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Review

Robust Goal Programming as a Novelty Asset Liability Management Modeling in Non-Financial Companies: A Systematic Literature Review

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Abstract: In addressing asset-liability management (ALM) problems, goal programming (GP) has been widely applied to integrate multiple objectives. However, it is inadequate in handling data changes in ALM caused by interest rate fluctuations. Therefore, a more robust and improved ALM optimization method is needed to manage fluctuations in financial ratios in ALM. This study introduces a novel approach by combining a systematic literature review (SLR) with the preference reporting items for systematic reviews and meta-analysis (PRISMA) method and bibliometric analysis to investigate the application of robust goal programming (RGP) models in ALM. The methodology involved planning, search and selection, analysis, and result interpretation as part of the SLR process. Using PRISMA, seven relevant publications were identified. The results of this SLR present a new strategy to combine goal programming and robust optimization to enhance ALM. Model development steps include constructing weighted goal programming (WGP) or lexicographic goal programming (LGP) models, using factor analysis for financial ratios, applying the best-worst method or simple additive weighting (SAW) for prioritization, and modeling financial ratio uncertainty with robust counterparts. This research provides a foundation for further studies and offers guidance to non-financial companies on adopting RGP for strategic ALM decisions and optimizing ALM under uncertainty.

Keywords: robust goal programming; asset liability management; financial performance; systematic literature review

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1. Introduction

Asset-liability management (ALM) is a classic problem in risk management [1,2] and an essential aspect of financial management in companies [3]. To meet the company's financial objectives, strategies for ALM are regularly developed, put into practice, reviewed, and adjusted while accounting for risk tolerance and other limitations [4,5]. Given its importance for a company's sustainability, ALM has become a key topic among practitioners and academics. Although ALM concerns have been extensively addressed in the literature, many intriguing issues require additional investigation [6] through a comprehensive SLR. The SLR includes a critical and transparent study of the body of information connected to the topic or research question [7–9] to obtain novelty.

A systematic literature review (SLR) related to ALM has been conducted, focusing on reviewing the ALM literature through multi-stage stochastic optimization [5]. The findings highlight the need for research on risk estimation in ALM modeling, particularly regarding unrealistic assumptions such as known parameter values derived from estimated historical data without accounting for estimation errors and the neglect of essential sources of uncertainty in stochastic modeling. Steuer and Na [10] conducted a bibliometric analysis of applying multiple financial decision-making techniques. One of the classification results obtained is goal programming (GP), which is used in ALM modeling by [11,12]. Sodhi [13] reviewed linear programming (LP) models for ALM, including methods for simplifying LP models and uncertainty representation in models. The results indicate that developing a model that includes interest rate scenarios on prepayment cash flows for mortgage-backed securities and hospital and other business bills is necessary. Aouni et al. [14] classified portfolio financial management models using goal programming. The results show that applying ALM to portfolio financial management can be modeled using GP. The model used was adapted from previous research [15–17]. The solution technique uses the weighting method. Ghahtarani et al. [18] conducted a literature review regarding the robust portfolio selection problem. The results show that the robust optimization approach can be used to apply ALM to the portfolio selection problem.

Asset-liability management (ALM) is essential for ensuring a company's long-term viability, necessitating effective optimization to reach targeted objectives. A multi-objective strategy is developed to tackle ALM challenges, focusing on maximizing profits while minimizing risks through comprehensive risk management [19]. In tackling multi-objective problems, the GP approach can be utilized to reduce the deviation variables that arise from the goal constraints [20]. During the process, uncertainty factors influence ALM, particularly fluctuations in interest rates. These changes can affect borrowing costs, investment returns, and spending decisions made by individuals, corporations, and government entities [21]. A practical method for tackling optimization challenges with uncertain data is the use of robust optimization (RO) [22]. RO has proven to be a dependable and efficient approach for solving real-world issues, such as production planning in unpredictable conditions [23].

Based on the SLR research description, no literature review specifically discusses the novelty of RGP in ALM modeling for non-financial companies. In addition, no one has used the PRISMA method for the selection process and bibliometric analysis for co-word analysis. This research aims to obtain novelty based on the state-of-the-art of previous studies using SLR, where the article selection process uses the PRISMA method and bibliometric analysis. The stages of SLR include the preparation (planning), search and selection, data analysis, and interpretation of results [7,9,24–27]. The article selection process uses the PRISMA method because it provides specific SLR requirements and enhances the quality of reporting [28–30]. Meanwhile, bibliometric analysis was used to identify relationships between previous research [2,24,31].

This research contributes to developing ALM RGP models in non-financial companies by providing insights from SLR. Furthermore, the SLR phases are fully explained, allowing other researchers to perform SLR. The research results are expected to improve the RGP model for ALM in non-financial companies. This article consists of four sections: the first is the introduction, which contains the research background of SLR on RGP for ALM in non-financial companies; the second explains materials and methods; the third presents the result and discussion; and the fourth is the conclusion.

2. Materials and Methods

2.1. Materials

Articles discussing GP for ALM in non-financial companies are the first study materials. Scopus and Science Direct are used for article searches. The criteria used in the search are that the articles are in English, GP models are covered, the article discusses ALM, balance sheets, and asset-liability management in non-financial companies are covered in the article, the articles are accessible, research articles, and articles published up to 2023. Scopus and Science Direct are used because of their popularity and reliability [32–34]. The mathematical models used for the modeling are the second study materials.

2.2. Methods

This study is a scientific exploratory investigation using GP modeling for ALM in non-financial companies using SLR. It aims to improve the transparency of the literature selection process that underpins the evaluation of GP models for ALM. This approach helps minimize subjectivity, clarifies which studies are included in the review, and reduces errors in selecting the literature used [35–38]. The stages carried out in an SLR are planning, searching, analyzing, and interpreting the results [7,9,24–27,39]. In the planning stage, the research questions are determined [32]. Formulating research questions is a crucial first step in guiding scientific investigations. The PICO framework, which consists of population/problem, intervention, comparison, outcome, and time, is used in the traditional evidence-based method [40].

The search strategy involved identifying digital libraries, creating keywords, and selecting articles [7,9,24–27]. The PRISMA method is used in the article selection process based on inclusion and exclusion criteria. PRISMA was chosen as it provides specific SLR requirements and enhances the quality of reporting [28–30]. The process of systematic search strategy using PRISMA comprises four primary stages: identification, screening, eligibility, and inclusion [26,30,41,42]. The article selection method is semi-automatic [43], with duplicate articles selected using the JabRef application and manual scanning of titles, keywords, and abstracts during the screening stage, followed by a full article review at the eligibility step. The chosen article's title, abstract, and keyword are read during the screening stage [44], and the full article is read at the eligibility stage.

The analysis stage in this research consists of bibliometric analysis and article analysis. The analysis aims to synthesize information from the included studies [45]. The bibliometric analysis in this research includes co-word analysis to identify relationships between studies [2,24,31]. VOSviewer (https://www.vosviewer.com/) and R-bibliometrix are used as tools for conducting bibliometric analysis. VOSviewer focuses on the visual representation of bibliometric maps and is particularly effective for displaying large-scale bibliometric maps in a clear and easily understandable way [46]. R-bibliometrix is an open-source tool in R designed for extensive science mapping analysis. It offers flexibility, frequent updates, compatibility with other R packages, and encourages collaborative development through GitHub [46]. The data analysis in this study was carried out by answering questions formulated at the planning stage and looking for research gaps, state-of-the-art, and novelty.

The interpretation stage presents analytical results highlighting research gaps from previous studies and the novelty guiding future research directions. In this study, the interpretation stage is elaborated in Section 3.2.

3. Results

3.1. Planning

This study aims to identify the gaps in the literature and the limitations of the current models by using the SLR to assess the GP for ALM in non-financial organizations. The following are the research questions in this study.

QR1. *What is the GP model for ALM in non-financial companies?*

QR2. *What method is used to complete the GP model for ALM?*

QR3. *What are the simulation results of the GP model for ALM?*

The research consists of three questions containing the PICO principle, namely problem (QR1), intervention (QR2), comparison (QR1 to QR3), and output (QR3).

3.2. Searching Strategy

The keywords used underwent several revisions. Initially, the keywords were "Robust Goal Programming", "assets", "liability", and "companies", as shown in Table 1.

Table 1. The number of papers using keywords "robust goal programming".

Stage	Keyword	Scopus	Science Direct
1	"Robust Goal Programming"	17	23
2	"Robust Goal Programming", "Assets", and "liability", and "management" and "companies"	0	0

Table 1 shows that searching with the keyword "Robust Goal Programming" resulted in 17 articles in the Scopus database and 23 articles in the Science Direct database, but none of them discussed RGP for ALM. Therefore, changes were made to the keywords described in Table 2, resulting in the number of articles collected at each stage.

Table 2. The number of papers obtained from the Scopus and Science Direct digital library.

Stage	Keyword	Scopus	Science Direct
1	"Goal Programming"	5495	7808
2	"Goal Programming" and "Assets"	105	953
3	"Goal Programming", and "Assets", and "liability"	25	133
4	"Goal Programming", "Assets", and "liability", and "management"	24	128
5	"Goal Programming", "Assets", and "liability", "management", and "companies"	6	86

Table 2 shows that the articles captured in the fifth stage were 92 articles, of which six were from Scopus and 86 were from Science Direct. The inclusion and exclusion criteria used in the selection process using the PRISMA method are described in Table 3.

Table 3. Inclusion and exclusion criteria.

Criteria	Symbol	List of Criteria
Inclusion	I1	English is the language of the articles
	I2	In the article, GP models are covered
	I3	The article talks about ALM
	I4	The balance sheets and asset liability management in non-financial companies are covered in the article.
	I5	Reachable
	I6	Research article
	I7	Articles published up to 2023
Exclusion	Ex1	Duplicate article

Table 3 shows the six inclusion criteria used for article selection: reading the title, keywords, and abstract at the screening stage. At the eligibility stage, all articles selected at the screening stage were read in their entirety. Selected articles at the eligibility stage are articles that can answer research questions at the planning stage and meet the inclusion criteria. At the same time, the exclusion criteria were applied for duplicate selection in the identification stages. Figure 1 displays the findings of the PRISMA technique search for articles.

Figure 1 shows that 92 articles were selected in the search process based on the keywords listed in Table 2. At the identification stage, the results indicated that no duplicate articles were found. During the screening stage, 4 articles were identified that met the inclusion criteria I1 to I7. The results of the selection at the eligibility stage yielded four articles that could answer the research questions. The next step involved conducting backward and forward citation processes by tracing articles that cite or are cited by the four selected articles. The results of these processes produced three additional articles that met the inclusion criteria I1 to I7 and could answer the research questions. The summary of 95 articles that were selected during the identification stage, along with the backward and forward process, is presented in the Table S1. In total, seven articles were obtained from the selection process using the PRISMA method [3,47–52]. The seven selected articles were able to answer the QR at the planning stage, so they were analyzed using biblimoetric analysis and manually by searching for the state-of-the-art based on research gaps and novelty.

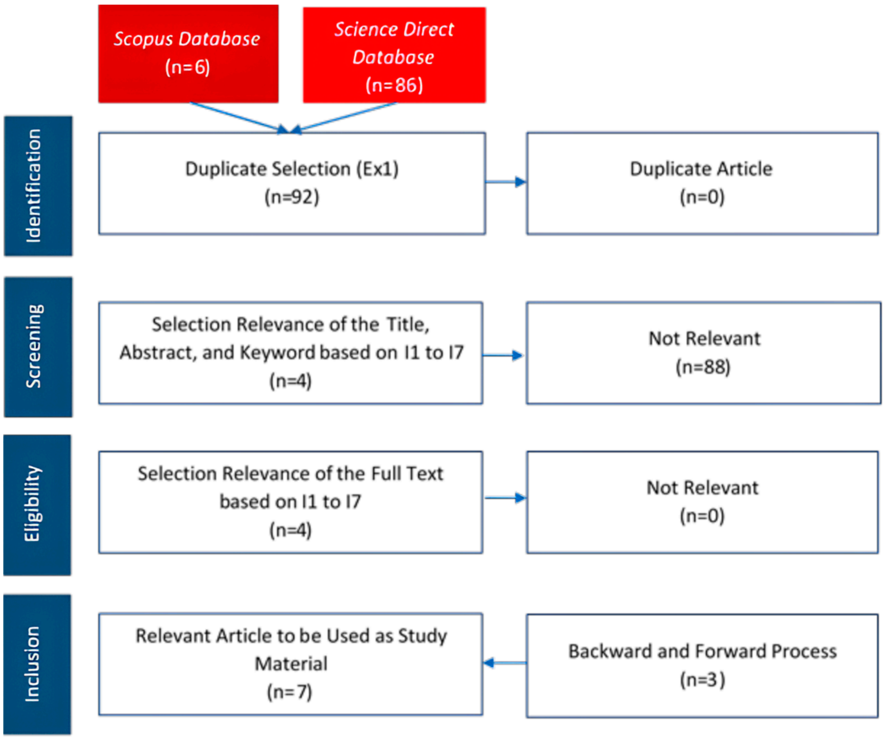

Figure 1. PRISMA diagram for the selection process.

3.3. *Analyzing*

Data analysis in this research consists of bibliometric analysis and article analysis.

3.3.1. Bibliometric Analysis

This subsection is divided into four parts: mapping of 95 articles, the evolution of themes in the 95 articles, analyzing the key themes in the 95 articles, and the most widely cited documents among the 7 selected articles.

- Mapping of 95 articles

The VOSviewer tool is used to conduct bibliometric analysis for mapping 95 articles selected during the identification process, as well as in the backward and forward citation processes. The analysis was performed on 95 articles obtained through the identification and backward and forward processes. The visualization of the bibliometric analysis results is presented in Figure 2.

Figure 2 shows many nodes of different sizes. The size of the nodes indicates how many terms have been discussed. Furthermore, as the nodes get bigger, the database contains a greater number of terms. The degree of link between these words is shown by the distance between each node. The co-word analysis conducted aims to identify the size of the node for the term “ALM” and the degree of relationship between the words. The visualization is presented in Figure 3.

Figure 3 illustrates that “ALM” in non-financial companies is underexplored, indicating its potential for further development, as evidenced by the relatively small size of the “ALM” node. The GP model is applicable for modeling ALM, as indicated by the connection between “ALM” and “GP model”. Moreover, the GP model for ALM has explicitly been applied to companies in Malaysia, as shown by the connection between "ALM" and "Malaysia".

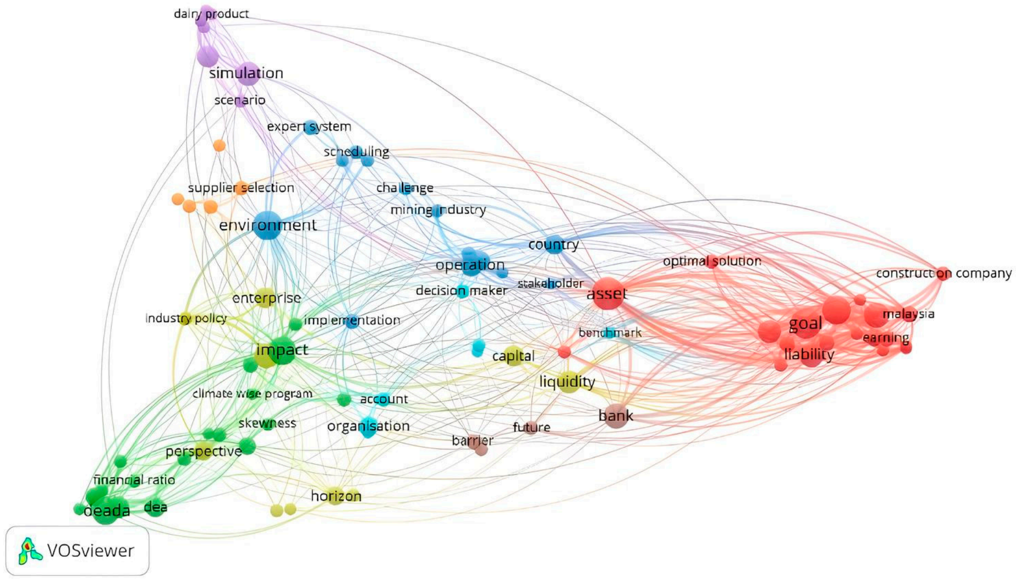

Figure 2. Mapping of 95 articles obtained in the identification process as well as the backward and forward processes.

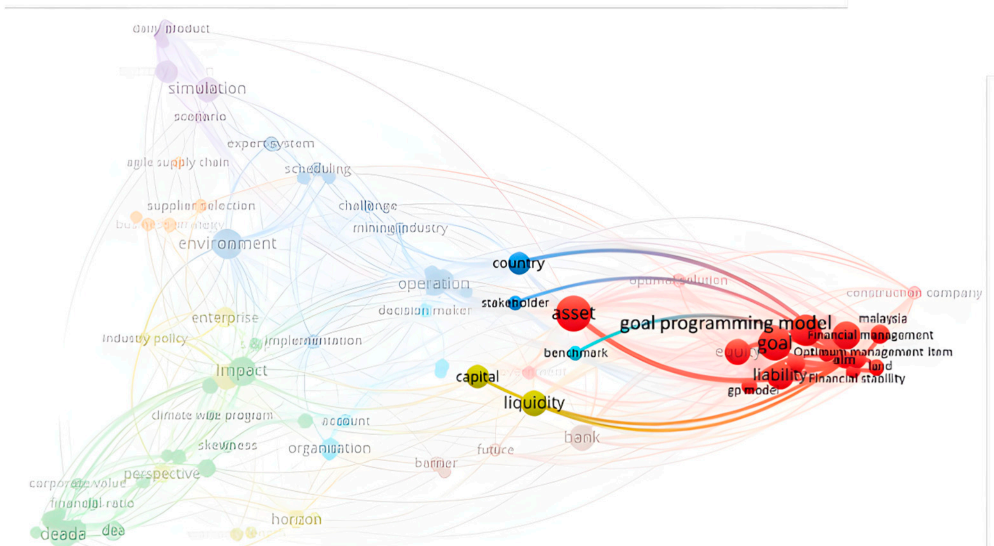

Figure 3. Mapping the GP framework for ALM using 95 articles.

- The Evolution of Themes in the 95 Articles

Figure 4 presents the evolution of themes in 95 articles. The thematic evolution is outlined across two distinct periods, namely 1976–2009 and 2010–2024. These divisions facilitate detailed observations of the changes and developments in the themes over the specified time intervals. This provides a comprehensive view of the dynamics of the main themes being explored in the literature. During the 1976–2009 period, one of the discussed themes was finance, which later evolved in the second period into a model. This evolution shows the relevance of the topic shifting from finance to mathematical models, which can be further explored in relation to these topics.

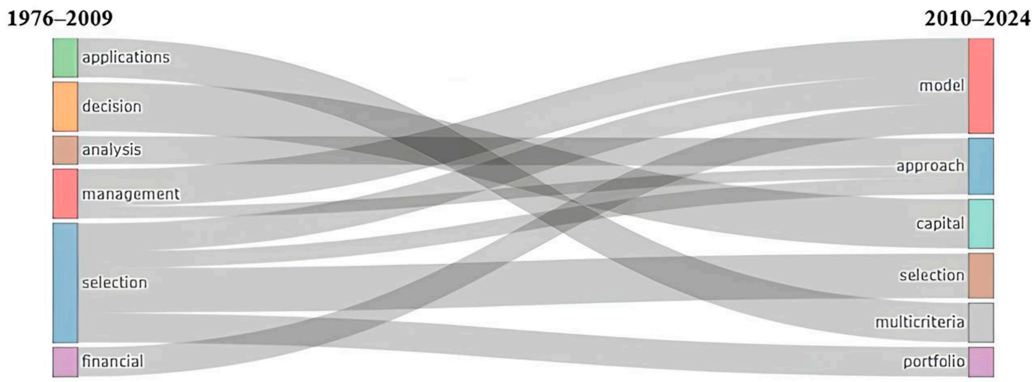

Figure 4. The evolution of themes in the 95 articles.

- Analyzing the Key Themes in the 95 Articles

The thematic mapping using the R-bibliometrix 4.4.1 software, as shown in Figure 5, illustrates the distribution of topics within 95 articles across various quadrants and clusters. Each theme is plotted according to its level of relevance (horizontal axis) and degree of development (vertical axis), and they are categorized into four quadrants. The motor themes in the top right quadrant, such as bankruptcy, financial performance, and decision making, exhibit high relevance and strong development. These themes are the most prominent and display strong internal connections, playing a key role in advancing research during the period. In contrast, basic themes in the bottom right quadrant, like supplier selection, decision making, finance, goal programming, and data envelopment analysis (DEA), have high relevance but relatively lower development.

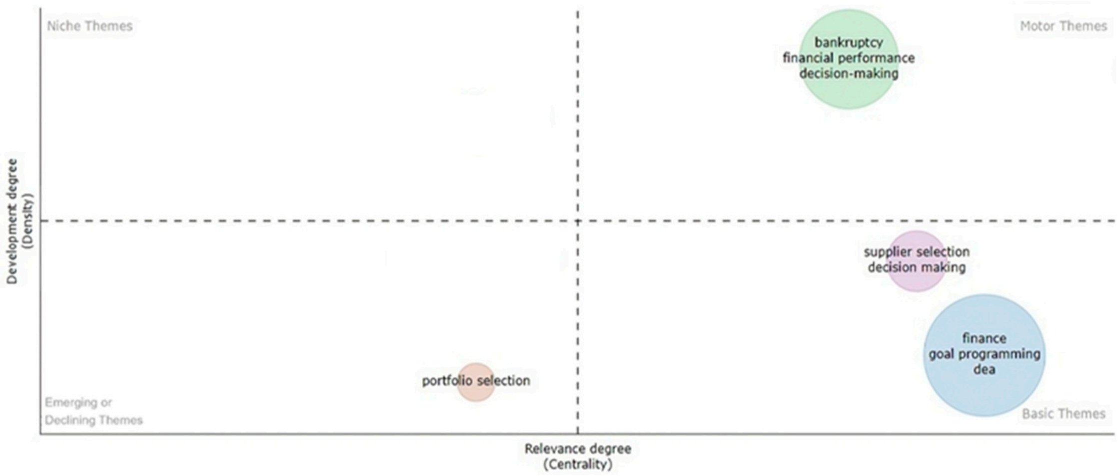

Figure 5. Mapping the key themes among the 95 articles.

The topic of financial performance with goal programming stands out as the dominant theme, demonstrating significant connections with other clusters throughout the period. Its illustration can be seen in Figure 6, the cluster network.

- The Most Widely Cited Documents among the 7 Selected Articles

The number of citations from the seven selected articles is illustrated in Figure 7, which was created using Microsoft Excel 2019. The topic of GP in ALM for non-financial companies was first introduced in 2018 and has gained increasing attention, particularly in 2022. The results show that the article by Alam [50] received the highest number of citations in 2022, with 9, followed by Prasad and Reddy [47], who garnered 3 citations. The two other articles, namely Lam, Lam, and Lee [49] and Hoe, Siew, and Fun [48], each received 2 citations. Notably, three of the articles, namely Lam Lee, and Lam [52], Lam, Lee, Lam, and Bakar [3], and Lam, Lee, and Lam [51], have yet to receive any citations, indicating that the application of GP in ALM is still not widely explored by other researchers.

Figure 6. Cluster Network the key themes among the 95 articles.

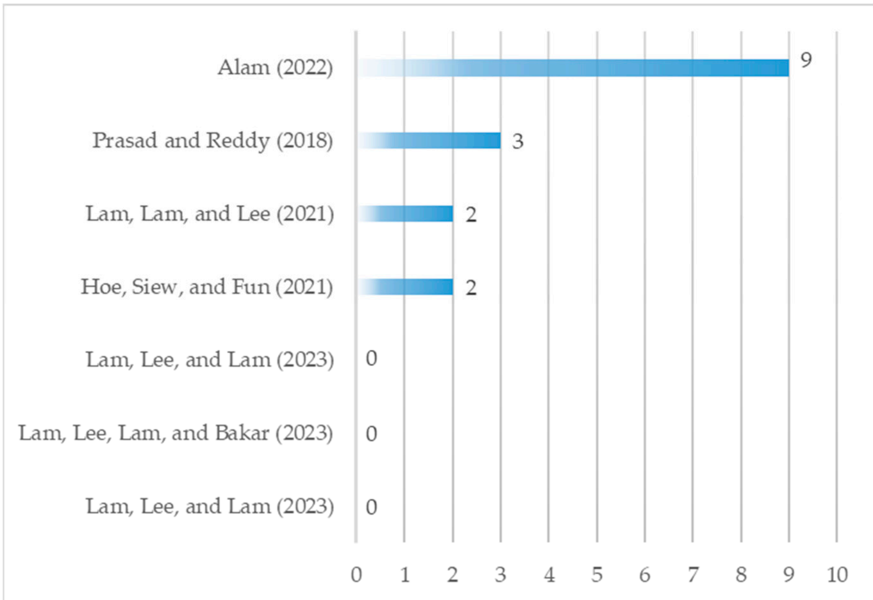

Figure 7. The most widely cited documents among the 7 selected articles [3,47–52].

ALM is sensitive to market interest rate movements [17], which influence future debt payments and impact financial performance. Additionally, interest rate changes introduce uncertainty [53], affecting the valuation of assets and liabilities. Given ALM's goal of ensuring financial performance to meet uncertain future obligations [6], robust goal programming techniques can be applied, focusing on worst-case scenarios of uncertainty [1]. This is an opportunity for developing the ALM model because, as shown in Figures 3 and 5, no node represents "robust goal programming (RGP)".

3.3.2. Data Analysis

The GP model for ALM was analyzed by following the model's development over the seven chosen papers since bibliometric analysis based on co-words cannot capture the evolution of research. In order to analyze the article, research questions from the planning stage described in Section 2.1 were addressed. The analysis of the article is described as follows:

- GP Model for ALM in Previous Research

The components discussed in the GP model consist of goals, decision variables, objective functions, and constraints from each GP model for ALM used in research [3,47–52]. The differences in goals for each GP model for ALM used in previous research are presented in Table 4.

Table 4. The differences in goals in previous research.

No	Item Goal	[47]	[48]	[49]	[50]	[3]	[51]	[52]
1	Maximizing Total Asset	√	√	√	√	√	√	√
2	Minimizing Liability	√	√	√	√	√	√	√
3	Maximizing Equity	√	√	√	√	√	√	√
4	Maximizing Income	√	√	√	-	√	√	√
5	Maximizing Operating Income	-	-	-	√	-	-	-
6	Maximizing Net Income	-	-	-	√	-	-	-

Table 4 shows the objectives intended to be achieved in the GP model in the previous article. The checkmark symbol indicates that the article uses the objectives listed in the goal column as objectives in the model. The table shows that the GP model for ALM in research [3,47–49,51,52] has the same goal, whereas [50] divides income into two, namely operating income and net income.

The decision variables in the GP model for ALM in previous research are presented in Table 5.

Table 5. The decision variables in previous research.

No	Decision Variables	[47]	[48]	[49]	[50]	[3]	[51]	[52]
1	Positive and negative deviation variables for each goal	√	√	√	√	√	√	√
2	The financial statements	√	√	√	√	√	√	√

The decision variables from the seven studies are the positive and negative deviation variables for each goal and the financial statements. The checkmark symbol indicates the use of decision variables in the previous article. The deviation variable cannot also be a fundamental variable. This shows that in the simplex method iterations in its solution, at most, one can be assumed to be positive. Let d_i^- and d_i^+ be the negative and positive deviation variables for the ith goal, respectively. Therefore, the achievement of the deviation variable is defined in Table 6.

Table 6. Achievement deviation variable.

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

Table 6 indicates that achieving the goal of minimizing the negative deviation variable occurs when the goal deviation variable equals zero and the positive deviation variable is more significant than zero. Achieving the goal of the positive deviation variable happens when the positive deviation variable of the ith goal equals zero, and the negative deviation variable is more significant than zero. The goal of combining the positive and negative variables for ith goal is accomplished when both the negative and positive deviation variables are equal to zero [47,50].

The objective function of the GP model for ALM in research [50–52] is formulated in Equation (1).

$$\min z = \sum_{i=1}^{m} p_i\left(d_i^+ + d_i^-\right). \tag{1}$$

The priority of the ith goal is denoted p_i. Referring to Tables 3 and 5, Equation (1) becomes Equations (2) and (3).

$$\min z_1 = d_1^- + d_2^+ + d_3^- + d_4^- + d_5^- + d_6^- + d_7^-. \tag{2}$$

Equation (2) is the objective function of the GP model for ALM used by [50]. The negative deviation variable for total assets is denoted d_1^-; the positive deviation variable for liabilities is denoted d_2^+; the negative deviation variable for equity, operating income, net income, profit, and the number of financial statements are denoted d_3^-, d_4^-, d_5^-, d_6^-, d_7^-, respectively. The priority of the goals is by the order of the goals.

$$\min z_1 = d_1^- + d_2^+ + d_3^- + d_4^- + d_5^- + d_6^-. \tag{3}$$

Equation (3) is the objective function in the GP model for ALM used in research by [51,52], where the positive deviation variable for liabilities is denoted d_2^+, the negative deviation variable for equity, income, profit, and the number of financial statements are denoted d_3^-, d_4^-, d_5^-, and d_6^-, respectively.

The objective function of the GP model for ALM in research [3,47–49] is presented in Equation (4).

$$\min z_2 = \sum_{i=1}^{m} w_i^+ d_i^+ + w_i^- d_i^-. \tag{4}$$

The weight of the ith goal positive deviation variable is denoted w_i^+, while the ith negative goal variable is denoted w_i^-. Referring to Tables 4 and 6, Equation (4) becomes Equation (5).

$$\min z_2 = w_1^- d_1^- + w_2^+ d_2^+ + w_3^- d_3^- + w_4^- d_4^- + w_5^- d_5^- + w_6^- d_6^-. \tag{5}$$

The weight of the positive and negative deviation variables can be determined using percentage normalization and the analytical hierarchy process (AHP) [47].

The constraints on the GP model for ALM from the seven previous studies are presented in Equation (6).

$$\sum_{j=1}^{n}\left(a_{ij}x_j + d_i^- - d_i^+\right) = g_i, i = 1,2,\ldots,m, j = 1,2,\ldots,n. \tag{6}$$

Equation (6) is a constraint for each ith goal. The negative deviation variable for the ith goal is denoted d_i^-; the positive deviation variable for the ith goal is denoted d_i^+; the weight of the ith goal in the jth year is denoted a_{ij}; the value of the financial report in the jth year is denoted x_j; and the limit for each goal ith is denoted g_i.

$$x_j, d_i^-, d_i^+ \geq 0, i = 1,2,\ldots,m, j = 1,2,\ldots,n. \tag{7}$$

Equation (7) is a non-negative constraint for each decision variable.

$$d_i^- \times d_i^+ = 0 \tag{8}$$

Equation (8) states that it is impossible to simultaneously achieve the goal for the negative and positive deviation variables. Therefore, one or both positive and negative deviation variables have a value of 0. The constraint in Equation (8) only exists in the GP model for ALM in [51].

- Method for Completing the GP Model for ALM in Previous Research

The method for solving the GP model for ALM is lexicography goal programming (LGP) [50–52], and weighted goal programming (WGP) research [3,47–49].

- Model Simulation Results in Previous Research

Differences in company types, periods, and data collection locations are presented in Table 7.

Table 7. Company types, periods, and data collection locations in previous research.

No	Reference	The Type of Company	Time	Location
1	[47]	Health care	2010–2017	Hyderabad
2	[48]	Electronic	2015–2019	Malaysia
3	[49]	Shipping	2016–2020	Malaysia
4	[50]	Chemical	2010–2020	Arab Saudi
5	[3]	Transportation	2017–2021	Malaysia
6	[51]	Highway	2017–2021	Malaysia
7	[52]	Construction	2017–2021	Malaysia

Table 7 indicates differences among company types regarding data collection time frames for simulations [3,51,52] spanning from 2017 to 2021, while the other four studies have varying periods. Annual financial data is used across all studies, with [50] covering an extended 11-year period compared to the others. Company locations include Malaysia [3,48,49,51,52], Saudi Arabia [50], and Hyderabad, which are mentioned explicitly in [47].

POM QM was used for optimizing solutions [47], while LINGO was employed in the remaining six studies. The output from the GP model simulation for ALM is detailed in Table 8.

Table 8. Model simulation results in previous research.

No	Reference	Simulation Results
1	[47]	• The objective function weights were calculated using percentage normalization, revealing the highest weight for profit at 48.780 and the lowest for financial statements at 1.529. The AHP method showed assets with the highest weight at 0.211 and financial statements with the lowest at 0.133. • The GP model simulation for ALM with percentage normalization shows no change in total assets and income. Liabilities can decrease by 0.00933 trillion, equity can increase by 0.00339 trillion, and profits by 0.00061 trillion. Financial statements can increase by 0.05695. • The GP model simulation for ALM with the AHP method shows no change in assets, liabilities, or income. Equity can increase by 0.013094 trillion, profits by 0.001878 trillion, and financial statements by 0.0564427 trillion.
2	[48]	• The GP model for ALM was applied to Malaysian electronics companies D&O, GTRONIC, UNISEM, and VITROX. • The simulation results show the desired goals were achieved for all companies. Liabilities for GTRONIC, UNISEM, and VITROX remain unchanged, while D&O's liabilities can be reduced by 4.063495 trillion.
3	[49]	• The Malaysian shipping companies studied were COMPLET, FREIGHT, and HARBOUR. • Simulation results show unmet goals in liabilities for COMPLET and HARBOUR, while FREIGHT failed to meet goals in liabilities, profits, and earnings.
4	[50]	• The GP model objective function for ALM prioritizes total assets, total liabilities, total equity, gross profit, operating income, net income, and financial statements. • Total assets, liabilities, operating income, and net income cannot be changed, while total equity, gross profit, and financial statements can increase by 0.04694982 trillion, 0.01220811 trillion, and 0.0118536 trillion, respectively.
5	[3]	• The transportation companies studied in Malaysia are CJCEN, COMPLET, and FREIGHT. • The simulation results indicate that COMPLET and FREIGHT did not achieve their liabilities and revenue goals, while HARBOUR still needs to address its liabilities.

Table 8. *Cont.*

No	Reference	Simulation Results
6	[51]	• The highway companies used for simulation are LITRAK, TALIWRK, and EDGENTA. • Simulation results show that LITRAK did not achieve its liabilities and earnings goals, TALIWRK did not achieve its liabilities, profit, and earnings goals, and EDGENTA did not achieve its liabilities goals.
7	[52]	• The highway companies used for simulation are DKLS, TRCS, and HSL. • The simulation results indicate that all three companies did not achieve their liability goals, and DKLS also failed to meet its equity goals.

The GP model simulation output for ALM [47], combined with percentage normalization and AHP methods, ensures that all goals are achieved. Both combination models state that assets and income cannot be changed, and the positive deviation variables for profit and equity are in accordance with financial management objectives where the value is not equal to zero.

The determination of weights in the GP model for ALM, as used in [48], needs to be more detailed. The model adopted in the study was sourced from [54]. According to the simulation results, the desired goals for each company were achieved. In the case of GTRONIC, UNISEM, and VITROX, liabilities cannot be changed, indicated by the maximum and minimum deviation variables being 0. However, for D&O, liabilities can be reduced by 4.063495 trillion.

The weights in the GP model for ALM in [49] should be elaborated upon in detail. According to the simulation results, the goals that were not achieved in COMPLET and HARBOUR companies were related to liabilities. In FREIGHT, the goals that were not achieved encompassed liabilities, profits, and earnings. This highlights the limitations of the GP model for ALM in fully meeting the companies' objectives. Future research could benefit from incorporating expert opinions to better align the GP model with the desired goals of the companies.

The determination of priorities in the GP model objective function for ALM in [50] is presented in Table 8. Based on the simulation results, it was found that each goal was met because it met the criteria in Table 6. Total assets, liabilities, operating income, and net income cannot be changed because the values of the positive and negative variables are equal to zero. Meanwhile, total equity, gross profit, and financial statements can be increased by 0.04694982 trillion, 0.01220811 trillion, and 0.0118536 trillion, respectively.

The determination of the weights in the GP model for the ALM in [3] is not explained in detail. The simulation results show that the liabilities and revenue goals for COMPLET and FREIGHT companies were not achieved. Meanwhile, goals that still need to be achieved at HARBOUR are liabilities. The results obtained reflect that COMPLET, FREIGHT, and HARBOUR companies can operate due to debt, so analysis is needed to prevent a spike in obligations that must be paid in the future.

The priorities in the GP model for ALM in [51] should be explained in detail. The simulation results show that the goals not achieved in LITRAK were liabilities and earnings. In TALIWRK, the goals that were not achieved were liabilities, profit, and earnings, while in EDGENTA, the goals that were not achieved were liabilities. The three companies observed that they could not achieve goal liabilities, which could mean excess debt for operating costs.

The priorities in the GP model for ALM in [52] should be explained in detail. The simulation results show that the liability goals for the three companies were not achieved, and the equity goals still needed to be achieved for the DLKS company. Failure to achieve the liability goal signals that the company's operational dependence on debt needs to be monitored for better financial stability.

4. Discussion

The goals in the GP model for ALM in previous research are based on the financial statements of each company observed, consisting of assets, liabilities, equity, profit, and earnings. The financial statements are found in [3,47–49,51,52], while ref. [50] divides income into two, namely operating income and net income. The parameters of each goal in the model simulation are obtained from the financial position report or balance sheet.

Financial reports display the company's financial situation on a specific day and the operations of the preceding period. However, the usefulness of financial reports resides in the fact that they cannot be used to forecast future conditions and earnings or, most importantly, as a basis for organizing measures that will enhance performance in the future [55]. Therefore, it becomes crucial to evaluate ratios that analyze the interrelationships within financial statements, aiming to assess the company's ability to meet its obligations. The four groups of ratios consist of liquidity ratios, asset management ratios, debt management ratios, and profitability ratios [56]. In previous research, none of the seven GP models for ALM discussed the four groups in ratio analysis.

Based on the analysis results, the GP models used for ALM in previous research were WGP and LGP. The GP model combines conflicting goals simultaneously. In the WGP model, weight is given to each undesirable deviation variable. In [47], the weight values were obtained using the percentage normalization and AHP methods. Meanwhile, in [3,48,49], simulation results from the WGP model for ALM [47] demonstrated that all goals could be achieved. Conversely, in [3,48,49], some goals still need to be achieved. In contrast, the LGP model allows the decision maker (DM) to rank objectives in lexicographic order based on their relative importance. When decision making takes place, the DM will add the obtained solution to the next solution according to the priority level. Subsequently, the process will progress until it produces the best compromise recommendation and reaches the final priority level [57]. In [50–52], only ref. [50] explained the priority order. The simulation results of the LGP model for ALM [50] show that all targets are achieved. However, in research [51,52], some goals still need to be achieved.

Based on the GP model analysis results for ALM, a research gap was obtained, described as follows.

1. Financial reports cannot be used to help predict future income, anticipate future conditions, and, most importantly, as a starting point for planning actions that will improve future performance [55].
2. In practice, the decision maker (DM) faces difficulty providing accurate weights, which is a challenging problem [58]. The weights in the GP model play a dual role, namely normalizing the goal measurement scale and explaining preferences [59]. In [3,48,49], the determination of weights is not explained, whereas in [47], AHP and percentage normalization are used. The percentage normalization in [47] in determining the weight of the objective function is done by dividing the deviation variable by the total target level. Determining the weights in the objective function using AHP has weaknesses, namely that the results vary depending on the form of the hierarchical structure [60].
3. Determining priorities in LGP needs to be explained in detail.
4. The simulation results from the GP model for ALM in the 7 selected articles indicate that the data used is dynamic and subject to change, such as fluctuations in interest rates or unexpected market conditions. These changes significantly impact decision making in asset and liability management, emphasizing the need for methods that can address these uncertainties. However, none of the seven articles discussed the effects of interest rate changes or the application of robust optimization, despite the fact that ALM heavily relies on market interest rate movements [17]. These fluctuations directly affect the size of future debt payments and can have a substantial impact on financial performance.

Based on the research gap previously studied, the state-of-the-art is the absence of a RGP model for ALM that is combined with financial ratios in the objective function and factor analysis to select the right financial ratio for the objective function. The best-worst method (BWM) to determine weights or using simple additive weighting (SAW) and normalization technique to determine priorities in the objective function. Therefore, the novelty that can be used to develop the GP model for ALM is based on previous studies in the following areas.

1. The financial ratios that can be used in the objective function are liquidity, asset management, debt management, and profitability ratios [55].
2. The financial performance of the organization is examined using ratio analysis. However, most ratios are not meaningful on their own unless they are contrasted with some benchmark, such as yearly trends [61]. Furthermore, selecting appropriate financial ratios is critical for accurately assessing financial performance [62]. This is because each type of non-financial company has different priorities for financial ratios in improving their financial performance. For example, pharmaceutical companies prioritize inventory turnover to increase profit [63], while the borrowing ratio has a significant effect on profit retention in manufacturing companies [64]. Working capital management and the fixed financial asset ratio impact profitability in the consumer goods sector [65]. The cost-on-revenue ratio, debt-to-equity ratio, and current assets ratio affect profit in real estate companies [66]. One way that can be done to reduce redundancies in variables is factor analysis, attempting to substitute specific behavioral variables with general and latent factors and preserving the majority of the source's information [61].
3. The weights on the GP model for ALM were determined using the BWM. The method uses pairwise comparisons between best and worst criteria/alternatives, and a consistency ratio is developed to ensure the reliability of the final results [60].
4. Employing the SAW alongside normalization techniques when LGP is applied in the basic ALM model framework. The SAW approach was chosen because it can improve the accuracy of the multi-criteria decision-making (MCDM) method's end outcomes [67].
5. The uncertainty component of the ratio analysis employed for each goal in the GP model for ALM has not been taken into account in any of the seven studies. The robust counterpart (RC) method is a robust optimization technique that can be applied [18,68,69]. Resolving the question of how and when an RC formulation of an indeterminate optimization problem can be stated as a computationally tractable optimization problem is the primary difficulty of the RC technique. The answer to this question will vary depending on how the indeterminate set is selected to represent the data conditions. A robust formulation can be achieved when the indeterminate data set is assumed to be in three sets described as a box, ellipsoidal, or polyhedral set [70].

Here are the steps for implementing the RGP model for ALM in non-financial companies:

1. Building a WGP or LGP Model

The first step in implementing the RGP model is to choose the appropriate model type between WGP and LGP. Non-financial companies need to identify the primary objectives of ALM, such as minimizing interest rate risk or maximizing asset returns. This model can be developed using optimization software such as Lingo QM for Windows 5.2, MATLAB Ver. R2024b, or Python 3.12.4, which supports goal programming. The inputs required include asset and liability data, as well as the financial goals to be achieved.

2. Determining Financial Ratios Using Factor Analysis

After building the model, the company needs to determine the financial ratios for the objective function. Factor analysis should be employed to reduce redundancy in financial variables and select the most relevant ratios. Tools like SPSS Statistics 30.0.0, R 4.4.1, or Python 3.12.4 with statistical analysis libraries can be used for this analysis. Ratios such as liquidity, solvency, and profitability can be evaluated, and the most significant ones for ALM should be chosen as model inputs.

3. Determining Weights for WGP Using BWM or SAW

At this stage, the company must determine the weights for each objective in the WGP model. If the BWM is used, the company needs to evaluate the best and worst objectives and then calculate the weights based on these preferences. Alternatively, the company can use SAW to normalize the data and prioritize objectives in LGP. Software like BWM Solver that can be implemented using Microsoft Excel 2019 or MATLAB Ver.R2024b can assist with these calculations.

4. Modeling Financial Ratio Uncertainty with Robust Counterpart

The final stage involves modeling the uncertainty in financial ratios using a robust counterpart approach. This allows the company to account for the variability in financial ratios due to interest rate fluctuations or other economic factors. The company can use software such as Python 3.12.4 or IBM CPLEX solver 22.1.1 to solve the optimization model augmented with this uncertainty, utilizing random number generation or data simulations to test different scenarios.

In comparative analysis with existing models, previous models only used GP without considering the uncertainty often encountered in ALM. Traditional GP models tend to focus on optimizing objectives without integrating the uncertainties that arise, such as interest rate fluctuations, which can significantly impact asset and liability management decisions. In contrast, the model proposed in this study combines GP with robust optimization (RO). This approach focuses on achieving ALM objectives and considers the uncertainty arising from interest rate changes. Consequently, the proposed model is more robust and better equipped to handle the variability of a dynamic financial environment.

Additionally, computing plays a crucial role in solving the proposed RGP model. Computation is necessary for several key stages, including generating random numbers to represent interest rate uncertainty and simulating data to model complex financial scenarios. By leveraging computational techniques, the RGP model can be evaluated more efficiently, and the results obtained are likely to be more accurate compared to the manual or static approaches used in traditional GP models. Thus, the combination of GP and RO and computational support provides a stronger and more realistic solution for managing ALM under uncertain conditions, such as those caused by interest rate changes. This model represents a significant advancement compared to previous models that relied solely on conventional GP.

The adaptability of the RGP model to other sectors is facilitated by considering financial ratio goal priorities through factor analysis. Data uncertainties in the financial sector can also be addressed using robust optimization. For example, in pension fund schemes, robust optimization can manage uncertainties in liabilities, mean returns, factor coefficients, and disturbances [70]. It also supports optimal investment allocation by considering uncertainties in return on assets, cumulative gross return on assets, and liabilities [71].

The limitations of this paper are that it only utilizes two academic databases, which restricts the scope of the research. The articles are obtained from Scopus and Science Direct due to their popularity and reliability [32–34]. Some important articles may not be included because they are unavailable in the selected databases. This results in findings that are not fully representative, as they do not cover all relevant research from other sources. The studies included in the SLR were selected based on too narrow criteria, focusing solely on articles discussing RGP and ALM in the context of non-financial companies without considering applications in other potentially relevant sectors. This could lead to bias in the review results, which may result in conclusions that are limited to a very specific context and fail to generalize the model. We chose to focus on non-financial companies because ALM is important not only in the financial sector but also in the non-financial sector.

5. Conclusions

This study presents SLR combined with the PRISMA method and bibliometric analysis to obtain the novelty of the GP model for ALM. The articles collected using the PRISMA method came from Scopus and Science Direct. The results obtained were seven articles. After that, the articles were analyzed using co-word analysis and bibliometric analysis with the help of VOSviewer and R-bibliometrix. In addition, selected articles were analyzed manually according to the answers to research questions compiled at the planning stage and compared to the GP model used for ALM modeling in non-financial companies, identifying research gaps so that state-of-the-art and novelty were obtained.

A review of seven articles discussing GP models for ALM indicates that no model can anticipate data uncertainty caused by interest rate changes, highlighting the need for further exploration in model development. To address uncertainty in ALM, robust optimization can be applied with specific uncertainty sets that reflect data variations. In real-world applications of RGP models, computational assistance is required to generate random numbers or simulate data. Model development can also focus on using financial ratios as the objective function, where factor analysis to select appropriate financial ratios for ALM in non-financial companies; BWM to determine weights in WGP; and SAW to prioritize in LGP.

The review aims to contribute to the understanding and practical application of the GP model for ALM and explore alternative models in its development. Additionally, it is expected to inspire future studies by identifying opportunities and fostering motivation in the field of GP models for ALM.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/computation12110220/s1, Table S1: A summary of 95 articles that were selected in the identification stage and the backward and forward process [3,10,14,47–52,72–157].

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