

Application of Linear Programming to Investment Portfolio Optimisation for an Indian Retail Investor

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Abstract

Indian households have a variety of investment options, ranging from fixed deposits and government small savings schemes to equity index funds, gold ETFs and REITs. However, most tend to be guided more by habit and imitating their surroundings rather than rational allocation. This paper uses linear programming (LP), a classic operations research methodology, to determine the optimal allocation of a budget of ₹10,00,000 across ten investment options available to an Indian retail investor as of October 2026. Expected returns were calculated using official and established sources and a risk score was assigned to each option (on a scale of 1 to 10).

The LP model was formulated to maximise expected annual return subject to thirteen constraints: a weighted average risk ceiling of 5, a 30% floor in government-backed instruments, a 25% cap on lock-in schemes, the statutory PPF limit and minimum and maximum holdings for each asset class. The model was solved using Excel Solver (Simplex LP). The solution was verified by a hand-worked simplex tableau and by the graphical method for a reduced two-variable form.

All three methods give the same optimum: ₹4.5 lakh in the Nifty 50, ₹2.5 lakh in NSC, ₹1.5 lakh in gold, ₹1 lakh in G-Secs and ₹50,000 in a fixed deposit. This earns an expected ₹1,04,895 a year (10.49%) at an average risk score of exactly 5.0. Sensitivity analysis shows that each 0.1-point increase in risk tolerance adds about ₹720 a year, and that the allocation stays unchanged for any equity return between 8.4% and 14.3%. Benchmarked against an all-FD saver, equal weighting, EPFO-style, NPS lifecycle and multi-asset fund allocations, the LP portfolio earns the highest return of all allocations that are constrained to respect the investor's constraints. The paper concludes that LP implemented in a ubiquitous Excel provides a transparent and verifiable basis for asset allocation for retail investors and advisers.

1. Introduction

1.1 Background to the study

Investment portfolio optimisation is the allocation of a given amount of money among competing assets to achieve optimal returns for an acceptable level of risk. Markowitz (1952) introduced the problem in its modern form, showing that the risk of a portfolio depends on the assets' co-movements, rather than just their individual risks. In practice, however, investors are subject to rules that have nothing to do with statistics: legal deposit limits, lock-in periods, minimum holdings for liquidity, floors set by regulators and comfort with respect to risk.

Linear programming (LP) is well suited to this rule-heavy setting. An LP model maximises or minimises a linear objective, such as total expected return, subject to linear constraints, such as a budget, a risk limit or an upper bound on

any one asset (Hillier & Lieberman, 2021). The simplex method of Dantzig (1963) solves such problems exactly, and the same algorithm is built into Microsoft Excel's Solver add-in. LP therefore provides a method that is both rigorous and accessible to an ordinary investor or adviser.

The Indian context makes the question of current interest. Savers in 2026 have choices among fixed deposits in banks, government small savings schemes (PPF, NSC, Monthly Income Scheme), sovereign and corporate bonds, gold ETFs, listed REITs and equity index funds. Their returns vary widely. Small savings rates have been static for ten consecutive quarters (S2), the 10-year G-Sec yield hit a two-and-a-half-year high of 7.19% on 30 September 2026 (S3) and gold rose about 12% in the first nine months of 2026 (S7), while the Nifty 50 fell over the same period. A retail investor who has these options before him needs a disciplined approach to combine them.

This study builds on Ogboi, Olurotimi, Olatunde and Blessing (2025), who used Excel Solver to solve a three-asset investment problem and a loan portfolio problem for Nigerian institutions with hypothetical data. The present paper uses the same LP methodology but applies it to real Indian data for ten instruments, adds in regulatory and liquidity constraints and solves the problem in three independent ways.

1.2 Statement of the problem

Most Indian households do not allocate their savings through any explicit optimisation. Many keep the bulk of their money in fixed deposits; others follow simple rules such as equal weighting or a fixed equity percentage. These approaches ignore the trade-off between return and risk and ignore binding real-world limits such as the ₹1.5 lakh annual PPF ceiling or the illiquidity of five-year schemes. The result is money left on the table or, at the other extreme, more risk than the investor can bear.

At the same time, existing LP studies of portfolio selection mostly use hypothetical data, few assets and simple constraints, and most are set outside India. There is therefore a need for a model that uses current Indian rates, covers the full range of retail instruments, encodes the constraints an Indian investor actually faces and shows the solution steps transparently.

1.3 Research objectives

1. To formulate a linear programming model for allocating ₹10,00,000 across ten Indian investment options using FY 2026-27 data.
2. To solve the model using the simplex method (Excel Solver and manual tableaux) and the graphical method, and to confirm that the methods agree.
3. To analyse the sensitivity of the optimal portfolio to the investor's risk tolerance and to the expected return on equities.
4. To compare the LP portfolio with real Indian portfolios and with other allocation methods, and to assess LP through a SWOT analysis.

1.4 Research questions

1. How should a moderate-risk Indian investor divide ₹10 lakh among the available instruments to maximise expected annual return?
2. Which constraints limit the optimal return, and what is each one worth?
3. How does the LP allocation compare with the portfolios of EPFO, NPS lifecycle funds and multi-asset mutual funds?

1.5 Scope of the study

- **Investor:** a single Indian resident retail investor, below 60 years of age, with a moderate risk appetite and ₹10,00,000 of investible surplus.

- **Instruments:** ten options: SBI fixed deposit, PPF, NSC, Post Office MIS, 10-year G-Sec, AAA PSU bonds, AA corporate bonds, listed REITs, gold ETFs and a Nifty 50 index fund. SCSS and Sukanya Samriddhi Yojana are excluded because only senior citizens and girl children are eligible.
- **Period:** a one-year investment horizon using rates and data available in October 2026 (Q3 of FY 2026-27).
- **Method:** single-objective linear programming solved in Microsoft Excel; the loan portfolio problem of the base paper is outside scope.

1.6 Limitations

- Risk is measured by an assigned score, not by variance or covariance, so diversification benefits between assets are not captured.
- Expected returns are point estimates. Equity and gold returns are long-run or recent averages and will not be realised exactly in any single year.
- Returns are pre-tax. PPF interest is tax-free, while FD, NSC and bond interest are taxable at slab rates; a post-tax model could change the ranking.
- The RBI's monetary policy decision of 7 October 2026 had not been confirmed when data were collected; a rate hike could lift FD and bond yields slightly (S9).

1.7 Significance of the study

The study would be of interest to investors and financial planners because it offers a ready template. Even if users alter the budget, risk ceiling or any rate in the accompanying Excel workbook and Solver returns a new optimal allocation in seconds. For students of operations research, it shows a complete LP workflow on real data, from formulation through simplex tableaux, graphical solution and sensitivity analysis. Finally, for researchers it adds Indian evidence to a literature that has relied largely on hypothetical cases.

2. Real-Life Context: How Indian Portfolios Are Optimised in Practice

Large Indian investors already allocate money within specified constraints, even if they may not always phrase it as linear programming. By studying how they do it, we see that the constraints used in this paper reflect practice and provide a genuine benchmark for the LP result.

2.1 Multi-asset mutual funds

SEBI's categorisation of mutual fund requires that a multi-asset allocation fund must have at least three asset classes with at least 10% each invested at all times (S14). This is a set of linear constraints of just the type used in this model: a minimum holding for each asset class.

ICICI Prudential Multi-Asset Fund is one of the largest hybrid funds in India with assets of ₹83,547 crore, and as of 30 April 2026 held 62.46% in equity, 7.90% in debt and 29.63% in other assets like gold, silver, REITs and cash (S10). The fund manager in effect maximises expected return subject to the SEBI floors and the fund's own risk limits, shifting weight between equity and commodities as valuations change.

SBI Multi Asset Allocation Fund has a mandate of 35% to 80% in equity. Its equity weight varied between 35% and 52% over two years, with about 30% in highly rated non-convertible debentures, 5% in government securities and about 11.4% in gold and silver ETFs, and it reported a 10-year CAGR of 12.17% (S11). Here the mandate range is a pair of bound constraints, and the fund manager chooses the point in it.

2.2 Retirement portfolios: EPFO and NPS

The **Employees' Provident Fund Organisation (EPFO)** manages a corpus of about ₹24.75 lakh crore as of March 2024 of which roughly 90.5% is in debt and 9.5% in equity ETFs tracking the Sensex and Nifty 50 (S12). Its investment is governed by the Ministry of Finance's pattern of investment, which sets upper and lower limits for each asset category. Capital safety dominates the objective.

The **National Pension System (NPS)** offers lifecycle funds whose equity share falls automatically with age. The aggressive LC75 fund starts at 75% equity, the moderate LC50 at 50% and the conservative LC25 at 25% up to age 35, each tapering towards government securities near retirement (S13). Each glide path is a set of age-dependent equity caps, again linear constraints.

Table 1: Asset allocation of real Indian portfolios

Portfolio	Equity	Debt	Gold others /	Governing constraint
ICICI Pru Multi-Asset Fund (Apr 2026)	62.46%	7.90%	29.63%	SEBI: $\geq 10\%$ in each of ≥ 3 classes
SBI Multi Asset Allocation Fund	35-52%	~35%	~11.4%	Mandate: equity 35-80%
EPFO (Mar 2024)	9.5%	90.5%	0%	Ministry of Finance pattern of investment
NPS LC75, age up to 35	75%	25%	0%	Equity cap falls with age
NPS LC50, age up to 35	50%	50%	0%	Equity cap falls with age
NPS LC25, age up to 35	25%	75%	0%	Equity cap falls with age
LP optimum (this study)	45%	40%	15%	Risk score ≤ 5 plus 12 other constraints

Sources: S10 to S14 (Appendix A). LP debt includes NSC, G-Sec and FD.

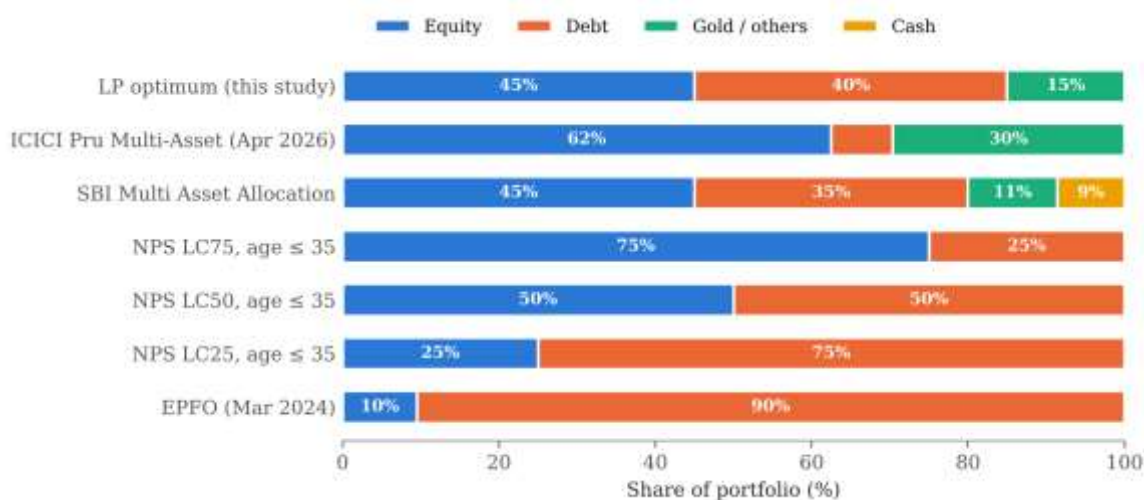


Figure 1: Asset mix of real Indian portfolios compared with the LP optimum

2.3 What these portfolios have in common

Each of these portfolios is the answer to a constrained optimisation problem. The objective differs (growth for a multi-asset fund, safety for EPFO, age-appropriate growth for NPS), but in every case a manager seeks the best outcome within hard limits on asset classes. The LP model in this study makes that process explicit for an individual investor. Its result, 45% equity, 40% debt and 15% gold, sits between the conservative EPFO and LC25 portfolios and the aggressive ICICI and LC75 portfolios, which is consistent with the moderate risk ceiling chosen. Section 8 compares their returns directly.

3. Why Operations Research Is the Most Suited Approach

Operations research (OR) involves making the best possible decision when resources are limited, and it achieves this by using mathematical models. A suitable example is selecting a portfolio. In this case, the resource is money, the decision concerns how much should be invested in each asset, and the constraints are determined by the investor's risk tolerance, their need for liquidity and the legal limits on certain instruments. Of the various OR techniques, linear programming (LP) is the one most appropriate for this problem, for the reasons stated below.

In the first place, the problem is linear in character since the expected return on the portfolio is a weighted sum of the returns on the individual assets, and both the weighted average risk score, the budget, and the individual holding limits are linear functions of the amounts invested; it is therefore possible to express the model as a linear programme without making any approximations. Moreover, the LP method can handle a large number of constraints together. This model includes thirteen such constraints, and it would be unreliable to attempt to find the optimal solution among them by relying on intuition or by trial and error; instead, the simplex method ensures that the solution is reached.

The answer it provides is precise. Because the feasible region of a linear programme is convex, any local optimum must also be the global optimum (Hillier & Lieberman, 2021), and so the solver will not end up with a suboptimal solution. The results are also easy to understand since shadow prices and reduced costs indicate the cost of each constraint and the reason why a particular asset is included in or excluded from the portfolio. This means that the recommendations can be audited, a feature that is important for a regulated adviser.

In practice, LP demands very little data. While mean-variance optimisation necessitates a complete covariance matrix, LP only requires expected returns and risk ratings, both of which are either already published or can be assigned. The method can also be carried out using ordinary software; the Simplex LP engine in Excel Solver solves it in seconds and thus makes the approach accessible to individual investors, students and small advisory firms, as well as to large institutions.

Each of the methods-statistical forecasting, simulation, and heuristic rules-contributes to solving one aspect of the problem, but none of them determines the best allocation subject to constraints. It is because linear programming does precisely that which it has been selected for use in this study.

4. Literature Review

4.1 Conceptual review

4.1.1 Linear programming

Linear programming is a technique which is used to optimise a linear objective function subject to a number of linear equality and inequality constraints (Hillier & Lieberman, 2021; Taha, 2017). Each linear programming model consists of decision variables, an objective function and constraints. The simplex method was devised by Dantzig in 1947 and is fully explained in Dantzig (1963). It starts at a corner point of the feasible region and then proceeds to adjacent corner points that yield a better objective function value, continuing until no further improvement is possible. When there are just two decision variables, the graphical method can be used as well: the constraints are plotted on a graph, the feasible region is identified, and the objective function value is examined at each corner point (Winston, 2004).

4.1.2 Assumptions of linear programming

The LP is based on five assumptions: proportionality implies that the return is in direct proportion to the amount invested; additivity means that the total return is equal to the sum of the returns from each individual asset; divisibility allows for fractional amounts; certainty states that all the coefficients are known in advance; and non-negativity prohibits short selling. The first three of these assumptions are reasonable when considering retail portfolios. Since certainty is the weakest assumption, this study carries out a sensitivity analysis to examine how much the results rely on it.

4.1.3 Investment portfolio performance

A portfolio is evaluated in terms of its return, its level of risk, and the way in which these two factors are balanced. Brinson, Hood and Beebower (1986) discovered that policy regarding the allocation of assets accounted for most of the changes in the returns of pension funds over time; it follows that the decision as to how to distribute money among different assets-which is the question examined in this study-is probably the most important one that an investor has to make.

4.2 Theoretical review

4.2.1 Modern portfolio theory

According to Markowitz in 1952, investors should select their portfolios from the efficient frontier, which is the collection of portfolios such that the expected return cannot be increased without also taking on greater variance. The model does, however, have a practical issue: it requires covariance between every pair of assets and is quadratic, which makes it difficult to compute. Sharpe, in 1963, proposed a simpler single-index model and subsequently demonstrated that the general portfolio problem could be approximated by a linear programme (Sharpe, 1971). Black and Litterman, in 1992, considered another issue-that the mean-variance weights are unstable-and dealt with it by combining the market equilibrium returns with the investor's own views.

4.2.2 Linear programming models of portfolio selection

Konno and Yamazaki (1991) substituted the variance with the mean absolute deviation; this caused the portfolio problem to become an LP, and when applied to data from the Tokyo stock market the results were similar to those of the Markowitz model. Young (1998) put forward a minimax rule which aims to maximise the worst-case return, a problem that can again be solved as an LP. Rockafellar and Uryasev (2000) did the same in the case of conditional value-at-risk, a measure of tail loss. Mansini, Ogryczak and Speranza (2014) reviewed twenty years of LP-based portfolio models and found that these models are efficient to compute and capable of dealing with real-world features such as transaction costs and holding limits. With regard to multi-objective approaches, Lee and Lerro (1973) used goal programming to select mutual fund portfolios, and Charnes and Cooper (1959) introduced chance-constrained programming to handle uncertain coefficients

4.3 Empirical review

Studies applying linear programming indicate that when solved using software that is widely available, it can achieve results better than those of standard portfolio allocations. Silva, Moreira and Francisco (2014) created a portfolio based on Brazilian companies that were included in governance and sustainability indices. This portfolio beat the IBOVESPA in 14 out of the 22 periods from 2007 to 2012, yielding an average return of 0.034 compared to -0.021 for the index. Oladejo, Abolarinwa and Salawu (2020) distributed \$15 million across seven assets, these including treasury bills, mortgage securities and construction loans. Their sensitivity analysis showed that a 5% change in interest rates caused portfolio returns to change by about 15% to 17%. Rabiou and Ajayi (2021) solved a portfolio selection problem using Microsoft Excel and therefore concluded that the method is suitable for financial managers. Williams, Atolagbe and Adeoye (2022) applied linear programming to loan and portfolio management for risk-averse investors, using data on ten firms from 2017 to 2021.

The most recent study is that of Ogboi et al. (2025), in which LP was applied using Excel Solver to two examples. The first example involved the distribution of ₦10 million among government bonds, real estate trusts and stocks, while the second concerned a ₦100 million loan portfolio for a bank. In the case of investment the return obtained was ₦9,30,000 with an average risk score of precisely 5.0, which shows that the risk constraint was indeed in operation. That said, there are some drawbacks: the data used were hypothetical, the model included only three assets, and the solution had not been independently verified.

4.4 Literature flow diagram

The connection between the studies discussed above is illustrated in Figure 2. The foundation of this framework consists of the early research into linear programming and into portfolio theory; from this come the LP formulations of portfolio selection, which in turn divide into multi-objective methods and into studies based on Excel applications. The applied studies eventually result in Ogboi et al. (2025), and the gaps identified in that paper are the ones that this study addresses. The full reference list is provided in RIS format so that it can be imported into Mendeley (see Appendix D).

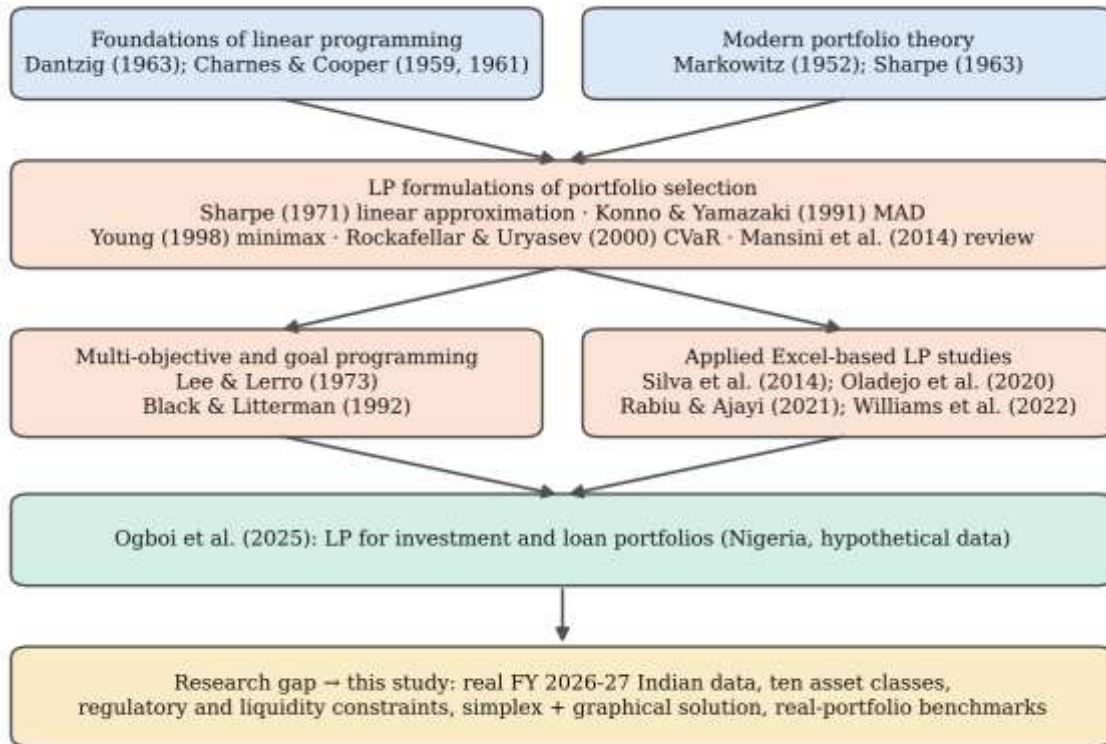


Figure 2: Literature flow diagram: from LP foundations to the research gap addressed in this study

Table 2: Summary of key empirical studies

Study	Context and data	Method	Key finding
Konno & Yamazaki (1991)	Tokyo stock market	Mean absolute deviation LP	Results close to Markowitz at far lower computing cost
Silva et al. (2014)	Brazil, 2007-2012	LP with index-based constraints	Beat IBOVESPA in 14 of 22 periods
Mansini et al. (2014)	Review of 20 years	LP portfolio models	LP handles real-world constraints efficiently
Oladejo et al. (2020)	US\$15 million, 7 assets	LP + sensitivity analysis	±5% rate change moves return by ~15-17%
Rabiu & Ajayi (2021)	Practical case	LP in Excel 2013	Excel makes LP practical for managers
Ogboi et al. (2025)	Nigeria, hypothetical	LP in Excel Solver	Optimum at average risk score 5.0

Study	Context and data	Method	Key finding
This study (2026)	India, real FY 2026-27 data, 10 assets	Simplex (Solver + tableau) and graphical	₹1,04,895 (10.49%) at risk score 5.0

Silva et al., Oladejo et al., Rabiun and Ajayi and Williams et al. are reported as summarised in Ogboi et al. (2025).

5. Research Gap

The following gaps in the literature are addressed by this study:

- 1. Hypothetical data.** Previous research, such as Ogboi et al. (2025), and applied studies use artificial returns and risk levels. This study uses publicly available FY 2026-27 rates from Ministry of Finance, NSE Indices, IBJA, RBI-regulated banks, and AMC bond trackers.
- 2. Too few assets.** Previous applied models consider only three to seven assets. In this study, a ten-instrument portfolio across six asset classes – deposits, Government small savings, sovereign bonds, corporate bonds, real estate, gold, and equity – is considered.
- 3. Missing Indian context.** Previous LP studies of applied portfolios have focused only on Nigeria, Brazil and Japan. No applied research considers the statutory limit of PPF, small saving lock-ins and the minimum allocation required similar to SEBI regulations.
- 4. No independent verification.** Previous studies report one Solver output only. The optimization problem is solved using the three independent methods (Solver in Excel, hand-computed simplex tableaux, and graphical method) and consistency in results demonstrated among all three.
- 5. No real-world benchmark.** None of the previous works has compared the LP solution with the actual holdings of investors. The LP solution in this study is benchmarked against the EPFO, NPS lifecycle fund allocation, and multi-asset funds.

6.1 Research design

The study uses a quantitative case study approach with analytical modelling in line with Ogboi et al. (2025). An investor situation is defined, data are gathered using secondary sources, LP model formulated and solved, and its solution validated and analyzed. Figure 3 outlines the procedure.

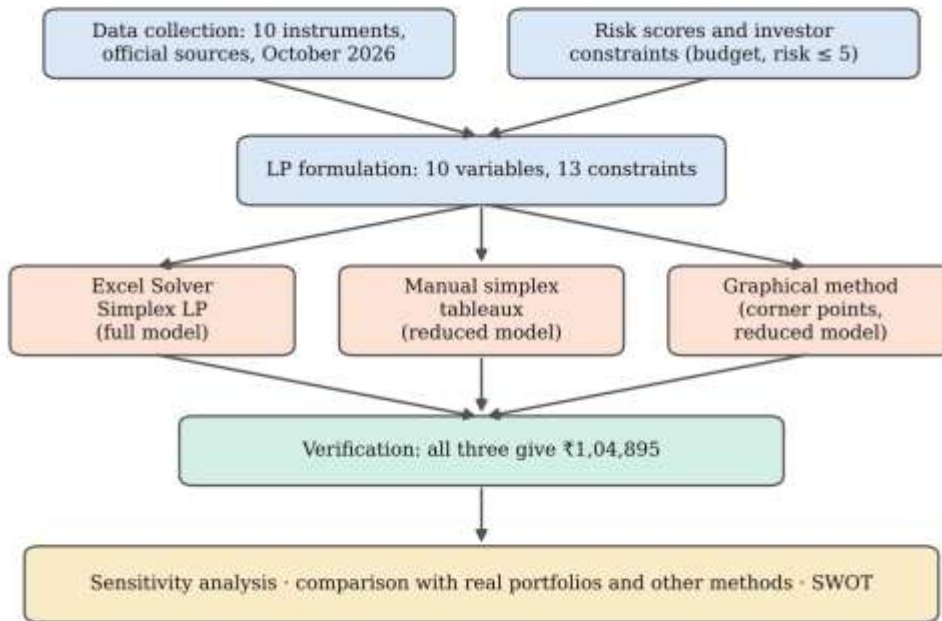


Figure 3: Research methodology flow

6.2 Data collection

The expected returns were collected from the time period of 1 to 8 October 2026 from the sources listed in Table 3 and Appendix A. As far as the case of fixed-income securities, current notified rate or yield in the market was considered. In the case of gold, the year to date percentage change for 2026 was taken as reported by IBJA, while in the case of Nifty 50, long-run total return was considered as published by NSE Indices because of the negative return on Nifty 50 in 2026.

Table 3: Dataset: investment options, expected returns and risk scores

Var	Investment option	Return	Risk	Basis (source)
x1	SBI Fixed Deposit (1 year)	6.25%	1	SBI retail card rate, 1-2 years (S5)
x2	Public Provident Fund (PPF)	7.10%	1	MoF notification, Q3 FY27 (S1, S2)
x3	National Savings Certificate (NSC)	7.70%	1	MoF notification, Q3 FY27 (S1, S2)
x4	Post Office Monthly Income Scheme	7.40%	1	MoF notification, Q3 FY27 (S1)
x5	10-year Government Security	7.19%	2	6.94% GS 2036 close, 30 Sep 2026 (S3)
x6	AAA PSU bond (5 year)	7.30%	3	ABSL AMC tracker, Aug 2026 (S4)
x7	AA corporate bond (5 year)	8.10%	5	ABSL AMC tracker, Aug 2026 (S4)
x8	Listed REITs	6.75%	6	Midpoint of 6-7.5% yield (S8)
x9	Gold ETF	12.00%	6	IBJA, 31 Dec 2025 to 1 Oct 2026 (S7)
x10	Nifty 50 index fund	12.74%	8	NSE TRI since 1995 (S6)

6.3 Assignment of risk scores

Following Ogboi et al. (2025), each option is given a risk score from 1 (lowest) to 10 (highest). Government-backed small savings and insured bank deposits score 1 because both principal and interest are fixed. The 10-year G-Sec scores 2: it carries no default risk but its price falls when yields rise. AAA and AA bonds score 3 and 5 to reflect credit risk. REITs and gold score 6 because their prices are volatile, and the Nifty 50 scores 8 as the most volatile option. The portfolio's weighted average score is used as its risk measure, and the investor's tolerance is set at 5, a moderate profile.

6.4 Model formulation

6.4.1 Decision variables

Let $x_1, x_2, \dots, x_{10}$ be the amounts in rupees invested in the ten options in the order of Table 3 (FD, PPF, NSC, MIS, G-Sec, AAA, AA, REIT, Gold, Nifty).

6.4.2 Objective function

Maximise the total expected annual return:

$$\text{Max } Z = 0.0625x_1 + 0.0710x_2 + 0.0770x_3 + 0.0740x_4 + 0.0719x_5 + 0.0730x_6 + 0.0810x_7 + 0.0675x_8 + 0.1200x_9 + 0.1274x_{10}$$

6.4.3 Constraints

With $B = ₹10,00,000$:

- (1) Budget: $x_1 + x_2 + \dots + x_{10} = 10,00,000$
- (2) Risk: $1x_1 + 1x_2 + 1x_3 + 1x_4 + 2x_5 + 3x_6 + 5x_7 + 6x_8 + 6x_9 + 8x_{10} \leq 5 \times 10,00,000 = 50,00,000$
- (3) Government-backed floor: $x_2 + x_3 + x_4 + x_5 \geq 3,00,000$ (30%)
- (4) Lock-in cap: $x_2 + x_3 + x_4 \leq 2,50,000$ (25%)
- (5) Liquidity: $x_1 \geq 50,000$ (5%)
- (6) PPF statutory limit: $x_2 \leq 1,50,000$
- (7) Sovereign anchor: $x_5 \geq 1,00,000$ (10%)
- (8) Credit limit: $x_7 \leq 1,00,000$ (10%)
- (9) Real estate limit: $x_8 \leq 1,00,000$ (10%)
- (10), (11) Gold band: $50,000 \leq x_9 \leq 1,50,000$ (5% to 15%)
- (12), (13) Equity band: $1,00,000 \leq x_{10} \leq 5,00,000$ (10% to 50%)
- Non-negativity: $x_i \geq 0$ for $i = 1, \dots, 10$

Constraint (2) is the linear form of the requirement that the weighted average risk score not exceed 5: dividing both sides by the budget gives $\sum w_i x_i / B \leq 5$, exactly as in Ogboi et al. (2025). Constraints (3) to (13) encode safety, liquidity, legal and concentration limits; their rationale is set out in the Parameters sheet of the workbook.

6.5 Solution in Excel Solver (simplex method, full model)

The problem was entered into the LP_Model worksheet of the workbook. Returns and risk scores are referred from the Data worksheet; the ten decision variables can be found in cells E5:E14 (changing cells). The objective function is formulated in cell G17 as SUMPRODUCT(returns, allocations); the Solver setup is shown below:

Table 4: Excel Solver parameters

Setting	Value
Set Objective	\$G\$17 (total expected return)
To	Max
By Changing Variable Cells	\$E\$5:\$E\$14
Subject to the Constraints	13 rows: \$C\$23:\$C\$35 compared with \$E\$23:\$E\$35 (=, ≤ or ≥)
Make Unconstrained Variables Non-Negative	Ticked
Select a Solving Method	Simplex LP
Reports	Answer and Sensitivity

Solver reported that it found an optimal solution satisfying all constraints. The result is presented in Section 7. It was confirmed independently using the HiGHS simplex solver, which returned the identical allocation and dual values.

6.6 Manual simplex method on the reduced problem

Ten variables and thirteen constraints are too many to pivot by hand on paper. Following standard practice, the variables that the full solution places at a bound are fixed: $x_1 = 50,000$ (at its floor), $x_5 = 1,00,000$ (at its floor), $x_9 = 1,50,000$ (at its cap) and $x_2 = x_4 = x_6 = x_7 = x_8 = 0$ (each has a positive reduced cost and is unattractive). The remaining decision is between the Nifty 50 (x) and NSC (y), measured in ₹ lakh.

Reduced problem. After removing the fixed holdings, ₹7 lakh of budget and 38.5 lakh risk units remain ($50 - 0.5 - 2.0 - 9.0$). The fixed holdings earn ₹28,315. The problem becomes:

$$\text{Max } Z' = 0.1274x + 0.077y$$

$$x + y \leq 7 \quad (\text{budget}); \quad 8x + y \leq 38.5 \quad (\text{risk})$$

$$y \leq 2.5 \quad (\text{lock-in}); \quad y \geq 2 \quad (\text{government floor: } 3 - 1 \text{ for G-Sec})$$

$$1 \leq x \leq 5 \quad (\text{equity band}); \quad x, y \geq 0$$

Removing lower bounds. Substituting $x = 1 + x_1'$ and $y = 2 + x_2'$ turns every constraint into a $\leq$ constraint with a non-negative right-hand side, so the slack variables s_1 to s_4 give an initial basic feasible solution without artificial variables. The objective gains a constant $0.1274(1) + 0.077(2) = 0.2814$:

$$\text{Max } Z' = 0.2814 + 0.1274x_1' + 0.077x_2'$$

$$x_1' + x_2' + s_1 = 4; \quad 8x_1' + x_2' + s_2 = 28.5; \quad x_2' + s_3 = 0.5; \quad x_1' + s_4 = 4$$

Table 5: Initial simplex tableau (Tableau 0)

Basis	Cb	x_1'	x_2'	s_1	s_2	s_3	s_4	RHS	Ratio
s_1	0	1	1	1	0	0	0	4	4.0000
s_2	0	8	1	0	1	0	0	28.5	3.5625
s_3	0	0	1	0	0	1	0	0.5	—
s_4	0	1	0	0	0	0	1	4	4.0000
Z_j		0	0	0	0	0	0	0	
$C_j - Z_j$		0.1274	0.0770	0	0	0	0		

Entering variable x_1' (largest $C_j - Z_j = 0.1274$). Minimum ratio $28.5/8 = 3.5625$ in row s_2 , so s_2 leaves. Pivot element = 8.

Iteration 1. The pivot row is divided by 8; every other row has the pivot column cleared (new row = old row – pivot-column entry $\times$ new pivot row).

Table 6: Simplex tableau after iteration 1 (Tableau 1)

Basis	Cb	x_1'	x_2'	s_1	s_2	s_3	s_4	RHS	Ratio
s_1	0	0	0.875	1	-0.125	0	0	0.4375	0.5
x_1'	0.1274	1	0.125	0	0.125	0	0	3.5625	28.5
s_3	0	0	1	0	0	1	0	0.5	0.5
s_4	0	0	-0.125	0	-0.125	0	1	0.4375	—
Z_j		0.1274	0.0159	0	0.0159	0	0	0.4539	
$C_j - Z_j$		0	0.0611	0	-0.0159	0	0		

Entering variable x_2' ($C_j - Z_j = 0.0611$). Rows s_1 and s_3 tie at ratio 0.5; the tie is broken by the lower row index, so s_1 leaves. Pivot element = 0.875.

Iteration 2. Pivoting on 0.875 gives Tableau 2.

Table 7: Final simplex tableau (Tableau 2): optimal

Basis	Cb	x_1'	x_2'	s_1	s_2	s_3	s_4	RHS
x_2'	0.077	0	1	1.1429	-0.1429	0	0	0.5
x_1'	0.1274	1	0	-0.1429	0.1429	0	0	3.5
s_3	0	0	0	-1.1429	0.1429	1	0	0
s_4	0	0	0	0.1429	-0.1429	0	1	0.5
Z_j		0.1274	0.077	0.0698	0.0072	0	0	0.4844
$C_j - Z_j$		0	0	-0.0698	-0.0072	0	0	

All $C_j - Z_j \leq 0$, so the tableau is optimal. s_3 is basic at value 0: a degenerate vertex where three constraints meet.

Reading the solution. $x_1' = 3.5$ and $x_2' = 0.5$, so $x = 1 + 3.5 = ₹4.5$ lakh in the Nifty 50 and $y = 2 + 0.5 = ₹2.5$ lakh in NSC. The reduced objective is $0.4844 + 0.2814 = 0.7658$ lakh = ₹76,580. Adding the ₹28,315 earned by the fixed holdings gives $Z = ₹1,04,895$, identical to the Excel Solver result. The values under the slack columns in the Z_j row are the shadow prices: ₹0.0698 per extra rupee of budget and ₹0.0072 per extra unit of risk allowance. Each tableau is reproduced with live formulas in the Simplex sheet of the workbook.

6.7 Graphical method on the reduced problem

Because the reduced problem has two variables, it can also be solved graphically. Each constraint is drawn as a line in the (x, y) plane, the feasible region is the area satisfying all of them and the objective is evaluated at each corner point (Figure 4).

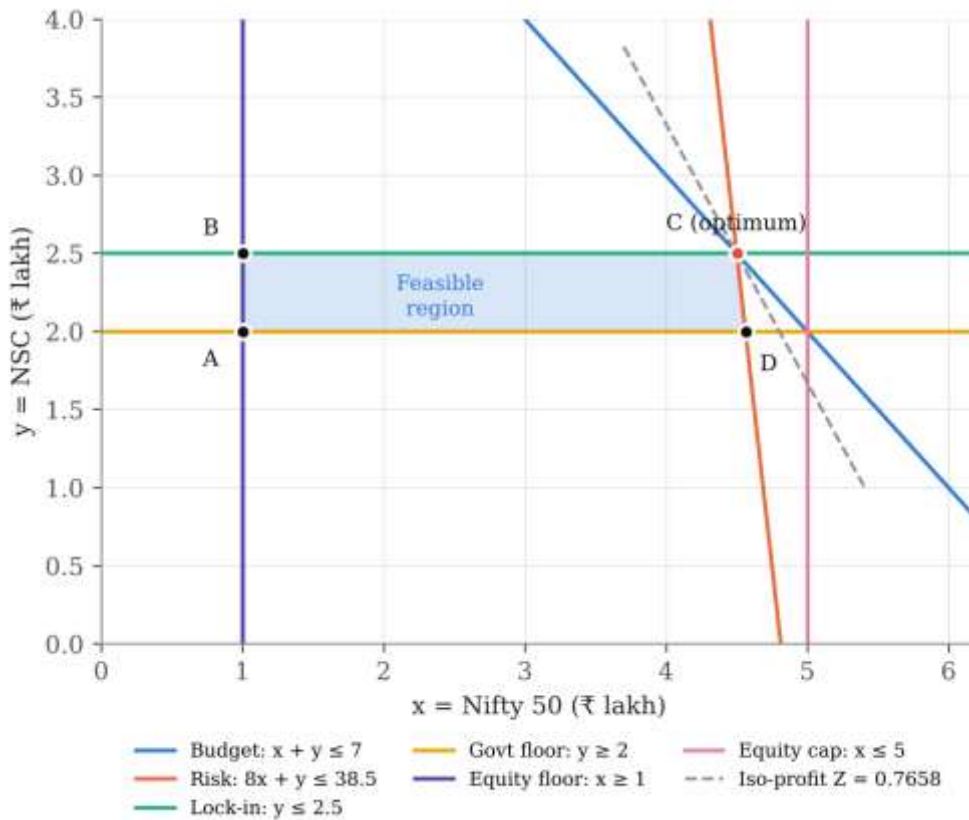


Figure 4: Graphical solution: feasible region ABCD and the optimal corner C

Table 8: Corner-point evaluation

Corner	x: Nifty (₹ lakh)	y: NSC (₹ lakh)	$Z' = 0.1274x + 0.077y$	Total return (₹)
A (equity floor, government floor)	1.0000	2.0000	0.2814	₹56,455
B (equity floor, lock-in cap)	1.0000	2.5000	0.3199	₹60,305
C (lock-in cap, risk and budget lines)	4.5000	2.5000	0.7658	₹1,04,895
D (government floor, risk line)	4.5625	2.0000	0.7353	₹1,01,841

Total return = $Z' \times ₹1 \text{ lakh} + ₹28,315$ from fixed holdings. Corner D: $8x + 2 = 38.5$ gives $x = 4.5625$.

The feasible region is the quadrilateral ABCD. Corner C gives the highest objective value, so the graphical method also selects ₹4.5 lakh in the Nifty 50 and ₹2.5 lakh in NSC, for a total return of ₹1,04,895. At C the budget, risk and lock-in lines all pass through the same point (4.5, 2.5), which explains the degeneracy seen in the simplex tableau. The iso-profit line through C (dashed) touches the feasible region only at C, confirming that it is the unique optimum.

7. Results and Interpretation

7.1 Optimal portfolio

Table 9: Optimal allocation of ₹10,00,000

Investment option	Allocation (₹)	Weight	Return (₹)	Risk units
Nifty 50 index fund	4,50,000	45%	57,330	36,00,000
National Savings Certificate	2,50,000	25%	19,250	2,50,000
Gold ETF	1,50,000	15%	18,000	9,00,000
10-year G-Sec	1,00,000	10%	7,190	2,00,000
SBI Fixed Deposit	50,000	5%	3,125	50,000
PPF, MIS, AAA, AA bonds, REITs	0	0%	0	0
Total	10,00,000	100%	1,04,895	50,00,000

Expected portfolio return 10.49%; weighted average risk score $50,00,000 / 10,00,000 = 5.00$.

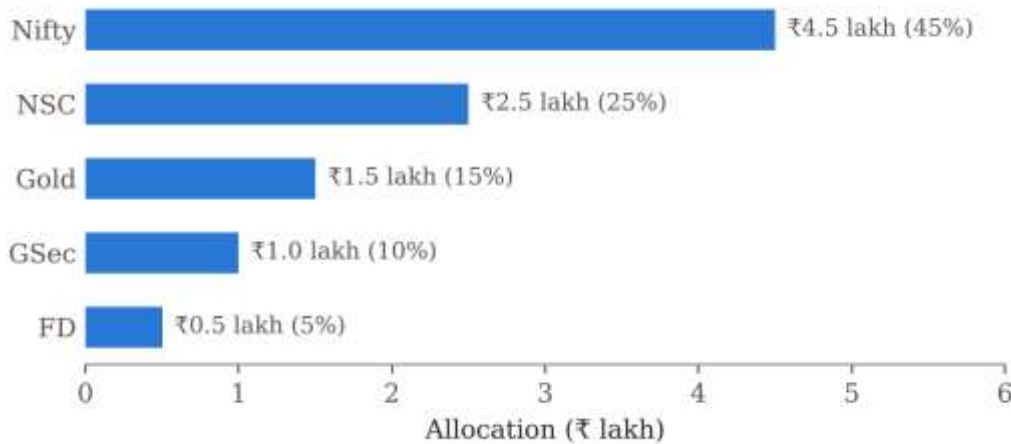


Figure 5: Optimal portfolio allocation

The optimal portfolio earns an expected ₹1,04,895 a year, a return of 10.49%, at an average risk score of exactly 5.0 which is the assumed investor's limit. Three methods (Excel Solver on the full model, the manual simplex tableau and the graphical method on the reduced model) give the same answer.

7.2 Constraint analysis

Table 10: Status of constraints at the optimum

Constraint	LHS	RHS	Slack	Status
(1) Budget	10,00,000	= 10,00,000	0	Binding
(2) Risk units	50,00,000	≤ 50,00,000	0	Binding
(3) Government-backed	3,50,000	≥ 3,00,000	50,000	Not binding
(4) Lock-in	2,50,000	≤ 2,50,000	0	Binding
(5) FD minimum	50,000	≥ 50,000	0	Binding
(6) PPF limit	0	≤ 1,50,000	1,50,000	Not binding
(7) G-Sec minimum	1,00,000	≥ 1,00,000	0	Binding

Constraint	LHS	RHS	Slack	Status
(8) AA bond cap	0	$\leq 1,00,000$	1,00,000	Not binding
(9) REIT cap	0	$\leq 1,00,000$	1,00,000	Not binding
(10) Gold minimum	1,50,000	$\geq 50,000$	1,00,000	Not binding
(11) Gold maximum	1,50,000	$\leq 1,50,000$	0	Binding
(12) Equity minimum	4,50,000	$\geq 1,00,000$	3,50,000	Not binding
(13) Equity maximum	4,50,000	$\leq 5,00,000$	50,000	Not binding

Six constraints bind. The **risk ceiling** is the decisive one: it stops equity at ₹4.5 lakh, ₹50,000 below its own cap. The **gold cap** binds because gold offers the best return per unit of risk (12% for a score of 6). The **lock-in cap** binds because NSC, at 7.7% with a risk score of 1, is the most efficient low-risk asset, so the model fills the 25% lock-in bucket with it. The **FD and G-Sec floors** bind because both earn less than NSC for similar risk, so the model holds only the required minimum.

7.3 Sensitivity analysis

7.3.1 Reduced costs: why some options are excluded

Table 11: Reduced costs and coefficient ranges

Option	Value (₹)	Reduced cost	Allowable increase	Allowable decrease	Interpretation
FD	50,000	0.0145	1.45 pp	No limit	Held only at its floor
PPF	0	0.0060	0.60 pp	No limit	NSC pays 0.6 pp more for the same lock-in
NSC	2,50,000	0	No limit	0.30 pp	Stays in until it yields less than MIS
MIS	0	0.0030	0.30 pp	No limit	Dominated by NSC
G-Sec	1,00,000	0.0123	1.23 pp	No limit	Held only at its floor
AAA bond	0	0.0184	1.84 pp	No limit	Needs 9.14% to enter
AA bond	0	0.0248	2.48 pp	No limit	Needs 10.58% to enter
REITs	0	0.0455	4.55 pp	No limit	Lowest return per unit of risk
Gold	1,50,000	-0.0070	No limit	1.11 pp	At cap while return $\geq 10.89\%$
Nifty 50	4,50,000	0	1.56 pp	4.34 pp	Mix unchanged for 8.40% to 14.30%

Reduced cost: rupees of return lost per rupee forced into the option (negative for a variable at its upper bound). pp = percentage points.

PPF is excluded even though it is tax-free, because the model is pre-tax and NSC pays 0.6 percentage points more within the same lock-in limit. On a post-tax basis for an investor in the 30% slab, PPF's 7.1% tax-free return would beat NSC's taxable 7.7%, and the model would switch; this is an important practical caveat. AA bonds would enter only if they yielded 10.58%, because each rupee in them uses five risk units that earn more in equity.

7.3.2 Shadow prices

The riskiest constraint has a shadow price of 0.0072 per risk unit. Substituting the ceiling of 5.1 (a lakh more risk units) raises the portfolio by 720 each year, and does so to a ceiling of 5.35, where equity hits its Rs 5 lakh limit. Bringing the

ceiling down by 0.1 costs 925, as the model switches out of the equity portfolio and into G-Secs - it is an optimization at a degenerate vertex in two dimensions. The gold cap has a shadow price of 0.007: an additional 10,000 risk units into gold yields 70. The government guarantee has a shadow price of zero: it is not binding.

7.3.3 Efficient frontier of the LP

The problem was re-solved with risk ceilings from 2.5 to 7.0 (Figure 6). Return increases at a constant rate of almost 4,625 per 0.5 risk increase until the ceiling hits 5.35. After that point the equity cap in turn becomes constraining and the return is fixed at 1,07,415. For risk ceilings below 2.05 the problem is infeasible, because even the minimum combination would risk that amount.

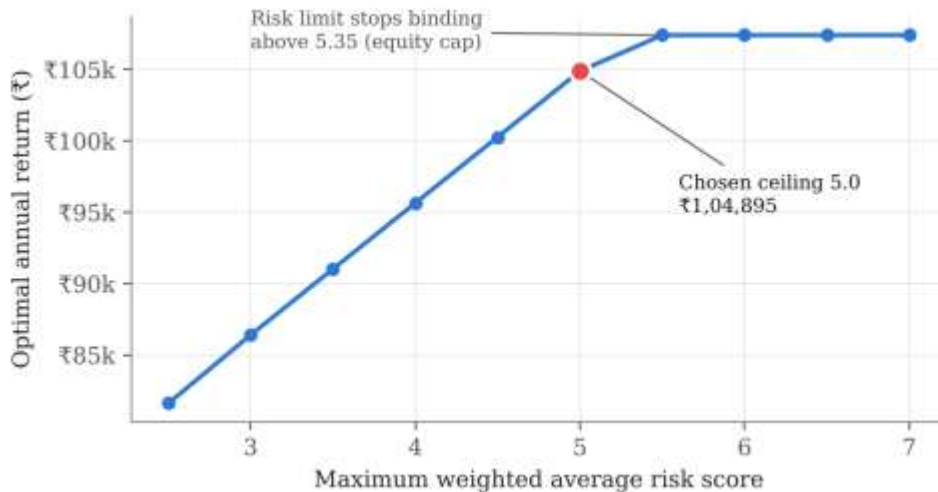


Figure 6: Optimal return at different risk ceilings

Table 12: Optimal return by risk ceiling

Risk ceiling	Nifty (₹)	NSC (₹)	G-Sec (₹)	Gold (₹)	FD (₹)	Return (₹)	Return %
2.5	1,00,000	2,50,000	1,00,000	1,40,000	4,10,000	81,605	8.16%
3.0	1,16,667	2,50,000	4,33,333	1,50,000	50,000	86,395	8.64%
4.0	2,83,333	2,50,000	2,66,667	1,50,000	50,000	95,645	9.56%
5.0	4,50,000	2,50,000	1,00,000	1,50,000	50,000	1,04,895	10.49%
6.0	5,00,000	2,00,000	1,00,000	1,50,000	50,000	1,07,415	10.74%

7.3.4 Scenario: lower or higher equity returns

Because the Nifty 50 fell in 2026, the equity return estimate deserves testing. The allocation does not change for any expected equity return between 8.40% and 14.30%; only the total return changes (₹88,065 at 9%, ₹97,065 at 11%, ₹1,10,565 at 14%). At 8% the model moves ₹1 lakh into AA bonds and trims equity to ₹3.93 lakh. At 6% equity falls to its ₹1 lakh floor and the money moves to AAA and AA bonds. At 16% equity rises to its ₹5 lakh cap and gold is cut to ₹80,000. The recommended mix is therefore robust across a wide band of equity outcomes.

7.4 Interpretation

Three observations which emerge: First, the investor's risk appetite is the ultimate limit on returns: it is the single limiting factor to equity, with each tenth of a percentage point averaging the equivalent of about 720-925 a year. Second, the allocation scores 1 for efficiency per unit of risk, not headline return: AA bonds are less risky but score poorly relative

to a NSC bond, as the risk budget is five times larger. Third, there is a quantifiable penalty for applying rules on liquidity: the 25% lock-in cap and 5% FD minimum score one for liquidity restrictions.

8. Comparison with Other Portfolios and Solution Methods

8.1 Comparison with real-world and rule-based portfolios

Each benchmark portfolio from Section 2 was mapped to the ten instruments on a ₹10 lakh base and evaluated with the same returns and risk scores (Table 13 and Figure 7).

Table 13: LP optimum compared with alternative allocations

Portfolio	Return (₹)	Return %	Avg risk	Constraints violated	Gap vs LP (₹)
LP optimum (this study)	1,04,895	10.49%	5.00	0	—
Equal weight (1/N)	82,530	8.25%	3.40	1	−22,365
Traditional saver (all FD)	62,500	6.25%	1.00	4	−42,395
Classic 60:40	1,05,200	10.52%	5.60	4	+305
EPFO-style (90.5% debt)	77,670	7.77%	3.02	3	−27,225
NPS LC50, age up to 35	99,980	10.00%	5.30	4	−4,915
ICICI Pru Multi-Asset style	1,20,910	12.09%	7.01	6	+16,015
SBI Multi Asset style	1,01,880	10.19%	5.37	3	−3,015

Mapping assumptions are listed in the Comparison sheet of the workbook. 'Constraints violated' counts breaches of the study's 13 constraints.

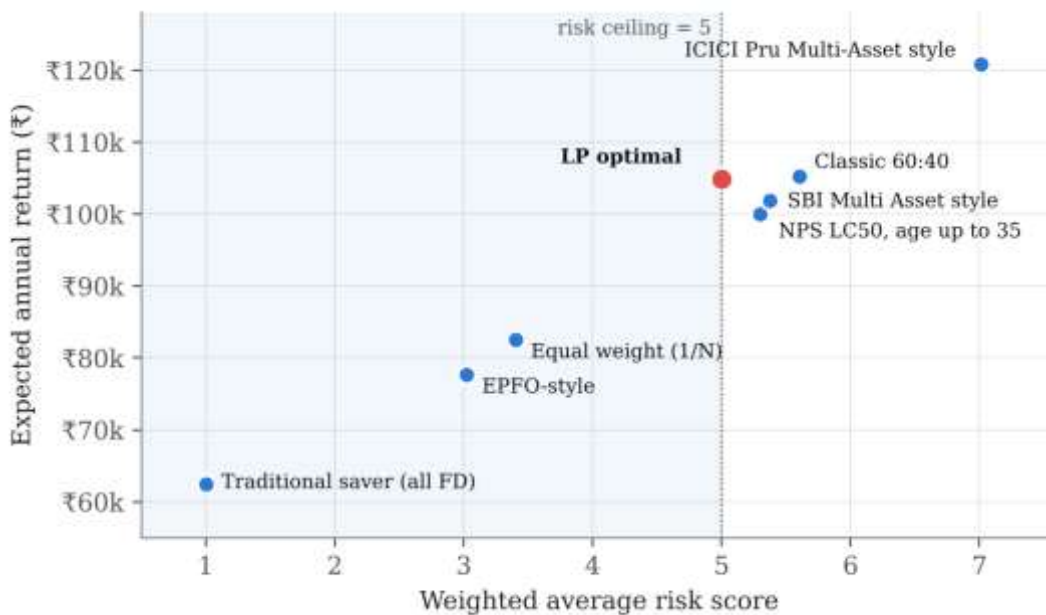


Figure 7: Return and risk of the LP optimum and benchmark portfolios

Among all portfolios that do not exceed the investor's risk limit of 5, the LP optimum offers the highest return. Equal weighing costs 22,365 a year, and the "traditional" all- FD approach costs 42,395 – 40% of what the return could be. Only two portfolios have higher returns: the classic 60:40 (by 305) and the ICICI-style multi-asset mixture (by 16,015), but both do so by surpassing the risk ceiling and breaching the equity or the gold cap, and are therefore not admissible for this investor. Here is the key and unique advantage of LP: it offers the optimal return that the investor can accept.

8.2 Comparison with other solution methods

Table 14: Comparison of portfolio optimisation methods

Method	Risk measure	Data needed	Strength	Limitation
LP, simplex (this study)	Linear risk score	Expected returns, risk scores	Exact optimum; shadow prices; runs in Excel	Ignores covariance
LP, graphical	Same	Same	Visual and intuitive	Two variables only
Markowitz mean-variance (QP)	Variance	Returns and full covariance matrix	Captures diversification	Sensitive to estimation error; needs non-linear solver
Mean absolute deviation LP	Absolute deviation	Historical return scenarios	Linear yet data-driven risk	Needs return history for every asset
Goal programming	Deviation from goals	Goals and priorities	Several objectives at once	Results depend on goal weights
CVaR optimisation (LP)	Expected tail loss	Return scenarios	Focuses on downside	Needs many scenarios
Heuristics (1/N, all FD)	None	None	Simple	No optimisation; ₹22,000 to ₹42,000 a year lower here

A mean-variance optimization would recognize the diversification benefit of mixing independent equities and gold, and would probably suggest that the LP risk score exaggerates the risk of the mixed investment. It depends on a covariance matrix, estimated on past data, and its weights are well-documented to be fragile (Black & Litterman, 1992). For the retail investor with published rates, and no database of historical rates, the LP methodology is more straightforward and intelligible, mean-variance and CVaR models follow naturally from it.

9. Conclusion and Recommendations

9.1 Conclusion

The research paper is concerned with showing how linear programming can be used when allocating investments among all the various investment instruments available in India. After applying the model to the actual data from the fiscal year 2026–27 for ten financial instruments and thirteen constraints, the model suggests that the investor should put ₹4.5 lakh into the Nifty 50 mutual fund, ₹2.5 lakh into NSC, ₹1.5 lakh into gold, ₹1 lakh into G-Secs and ₹50,000 into a fixed deposit. The portfolio is expected to yield an annual income of ₹1,04,895 (that is, 10.49%), and has a risk level of precisely 5.0.

The following are the answers to the research questions. First, the fund allocation mentioned above is optimal for the typical investor and this has been established through three different methods. Second, the upper limit of the risk level is the most important constraint, with a value of approximately ₹720 per point; the gold limit, the lock-in limit and the minimum limits for FD/G-Sec investments are also binding.

Thirdly, when the investor's constraints are taken into account, the LP portfolio outperforms all the benchmarks, exceeding the Equal Weighted Portfolio by ₹22,365 each year, the EPFO-like portfolio by ₹27,225 and the Full FD by ₹42,395. Portfolios that deliver higher returns, for example the ICICI-style multi-asset portfolio, have done so by assuming a higher level of risk than the risk level acceptable to the investor.

The paper confirms the result obtained by Ogboi et al. (2025) that using LP with Excel Solver constitutes a practical method of portfolio selection and extends that study by incorporating practical data from India.

9.2 Recommendations

1. **Investors and their advisers** ought to use an LP Model, such as the one mentioned above, to carry out asset allocation consciously rather than automatically and should recalculate it every quarter when the rates of small savings and bond yields are adjusted.
2. **Risk tolerance must be chosen consciously** since it is the most important factor affecting return of all the various inputs; the frontier in Figure 6 shows the investor exactly how much return he obtains for every extra unit of risk tolerance.
3. For investors who are in higher tax brackets, **tax considerations should be made**, as the after-tax returns could affect the standing of the PPF and NSC.
4. **Further research** should involve extending the LP model to use historical data and incorporate mean-variance or CVaR as a risk measure, as well as looking at multiple time periods and applying goal programming for investors who have several goals.
5. **Educational institutions** should make use of case studies involving LPP and real data to teach students on operational efficiency.

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Appendix A: Data Sources

All web sources were accessed between 1 and 8 October 2026.

- S1** Ministry of Finance, Department of Economic Affairs (Budget Division). Office Memorandum F.No.1/4/2019-NS dated 30.09.2026: interest rates on Small Savings Schemes for Q3 FY 2026-27 unchanged. Rates as listed by Indian Bank. <https://indianbank.bank.in/en/interest-rates-for-small-savings-schemes>
- S2** Press Trust of India (via Free Press Journal), 30 Sep 2026. Small savings interest rates unchanged for Oct-Dec; PPF at 7.1 per cent, NSC at 7.7 per cent. <https://www.freepressjournal.in/business/small-savings-interest-rates-unchanged-for-oct-dec-ppf-at-71-per-cent-nsc-at-77-pc>
- S3** Trading Economics, 1 Oct 2026. India 10Y yield hits over 2-year high (benchmark 6.94% 2036 bond closed at 7.19%). <https://tradingeconomics.com/india/government-bond-yield/news/588615>
- S4** Aditya Birla Sun Life AMC. Daily Fixed Income Tracker, 10 Aug 2026 (yield monitor for AAA and AA corporate bonds). <https://mutualfund.adityabirlacapital.com/-/media/knowledgecenter/pdf/all-about-market/daily-fixed-income-tracker-10-aug-2026.pdf>
- S5** Paisabazaar. SBI FD interest rates (retail domestic deposits below Rs 3 crore). To be confirmed against sbi.co.in. <https://www.paisabazaar.com/fixed-deposit/sbi-fd-rates/>
- S6** NSE Indices Ltd. Nifty 50 Whitepaper 2026 (Total Return Index annualised 12.74% since inception, Nov 1995 to Feb 2026). https://niftyindices.com/docs/default-source/indices/nifty-50/nifty-50-whitepaper_2026.pdf
- S7** India Bullion and Jewellers Association (IBJA) benchmark rates as reported by Patna Press (31 Dec 2025 level) and Bajaj Broking (1 Oct 2026 level). <https://patnapress.com/gold-silver-price-july-2-2026-ibja/> ; <https://www.bajajbroking.in/blog/gold-rate-today-15-may>
- S8** Business Standard, report on CREDAI-Anarock study: Indian REITs deliver 6 to 7.5 per cent average distribution yields. <https://www.business-standard.com/topic/reit>

S9 Reserve Bank of India MPC: repo rate 5.25% (Aug 2026 review); October 2026 decision due 7 Oct 2026 (Outlook Money). <https://www.outlookmoney.com/banking/rbi-mpc-october-2026-key-things-to-know-ahead-of-policy-decision>

S10 ICICI Prudential Multi-Asset Fund factsheet as on 30 Apr 2026 (equity 62.46%, debt 7.90%, others 29.63%; AUM Rs 83,547 crore), via Kotak Mahindra Bank factsheet page. https://www.kotak.bank.in/MF_Factsheet/EQUITY/scheme-pages/ICICI-Prudential-Multi-Asset-Fund.html

S11 Outlook Money. SBI Multi Asset Allocation Fund: Growth without the grind (equity mandate 35-80%, about 30% in highly rated NCDs, 5% G-Secs, 11.4% gold and silver ETFs). <https://www.outlookmoney.com/invest/olm-50/sbi-multi-asset-allocation-fund-growth-without-the-grind>

S12 Angel One. Investments made by EPFO: corpus of Rs 24.75 lakh crore, about 90.5% debt and 9.5% ETFs (March 2024). <https://www.angelone.in/news/market-updates/investments-made-by-epfo-manages>

S13 Business Standard. NPS, UPS get 75% equity option for govt staff (lifecycle fund equity caps by age). https://www.business-standard.com/finance/personal-finance/nps-ups-get-75-equity-option-for-govt-staff-here-s-what-it-means-125102800843_1.html

S14 Tata Mutual Fund. The 10% rule: understanding SEBI's multi-asset mandate (SEBI circular on categorisation of schemes, 6 Oct 2017). <https://www.tatamutualfund.com/blogs/10-rule-understanding-sebis-multi-asset-mandate>

Appendix B: Complete LP Model and Excel Implementation

Model in matrix form. Maximise $Z = c^T x$ subject to $Ax \leq b$, $\Sigma x = B$ and $l \leq x \leq u$, where c is the vector of expected returns in Table 3, A contains the risk, government-backed and lock-in rows and l and u hold the individual bounds of constraints (5) to (13).

Table 16: Workbook guide (Portfolio_LP_Model_India_2026.xlsx)

Sheet	Contents
Cover	Contents, colour legend, key results and Solver instructions
Data	Ten options with return, risk score, basis and source
Parameters	Budget, risk ceiling and every allocation limit with rationale (editable)
LP_Model	Full model pre-loaded for Solver; objective; constraint check with slack and status
Simplex	Reduced problem derivation and three tableaux computed with live formulas
Graphical	Corner-point evaluation and chart of the feasible region
Sensitivity	Reduced costs, shadow prices, coefficient ranges, frontier and equity scenarios
Comparison	LP portfolio against seven benchmark allocations; method comparison
Real_World	Allocations of ICICI, SBI, EPFO and NPS portfolios with sources
Sources	All data sources and academic references

Appendix C: Verification of the Optimum

The optimal solution was obtained and checked in four ways: (1) Excel Solver, Simplex LP engine, on the full model; (2) the HiGHS dual simplex solver in Python (SciPy), which returned the identical allocation and dual values; (3) the hand-worked simplex tableaux of Section 6.6, which reach optimality in two iterations; and (4) the graphical corner-point method of Section 6.7. All four give $Z = ₹1,04,895$. The workbook recomputes the simplex and graphical results from the Data and Parameters sheets, so a change to any input is reflected immediately.



Appendix D: Reference Library for Mendeley

The references above are supplied as a separate RIS file (references_mendeley.ris). To import: in Mendeley Reference Manager choose File > Import > RIS, select the file, then use Mendeley Cite in Word to insert citations and regenerate the reference list in any style.