

A Review of Finance and Wealth Management in India Using Artificial Intelligence

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Abstract

Artificial Intelligence has moved out of the laboratory and into the daily machinery of Indian finance. What began at the Dartmouth Conference of the 1950s as an enquiry into whether machines could imitate human reasoning now underwrites credit decisions, portfolio rebalancing, fraud interception and goal-based financial planning for millions of Indian households. This paper is a systematic review of the ways in which AI is being used to create and manage wealth in India, and of the conditions under which that use is likely to remain sound. Twenty-two scholarly studies, regulatory documents and industry reports published between 2016 and 2026 were selected through a defined search protocol and subjected to structured content analysis.

The six dimensions used for coding each source was thematic focus, year of publication, applied AI technique, functional area of wealth management addressed, direction of report impact, and barriers identified. The coded evidence was later summarized using frequency distribution, percentage and a two tailed binomial significance test. The review finds that AI is powering Indian Wealth Management up a well-defined maturity hierarchy. Fraud detection, credit scoring and conversational customer service are operationally mature, algorithmic portfolio construction and robo-advisory are in a stage of rapid but uneven growth, truly holistic, tax-aware, life cycle financial planning is still largely aspirational.

We rejected the null hypothesis, with 19 of the 22 sources reporting a positive and material contribution of AI to financial outcomes (86.36 percent, two tailed Binomial $p < 0.001$). Conversely,

72.73 percent of the sources recognized algorithmic opacity as a constraint, 68.18 percent recognized data privacy and security, and 59.09 percent recognized low financial digital literacy levels. The Securities and Exchange Board of India's February 2025 amendments and RBI's August 2025 FREE-AI framework were found to be the most significant governance interventions of the Period. The research finds the limits on India's AI-in-Finance potential are now more regulated by explainability, data governance and investor understanding than modelling skill, suggesting future research should move away from showcasing AI effectiveness toward defining the requirements for its trustworthiness.

Keywords: Artificial Intelligence, Wealth Management, Robo-Advisory, Machine Learning in Finance, FinTech India, Responsible AI, Portfolio Optimisation

1.1 Introduction

The expression "Artificial Intelligence" entered academic vocabulary at the Dartmouth Conference of the 1950s. The assembly was basically a gamble, that a machine could be built to mimic human thought. The early approaches were based on formal logic and hand coded rules, codifying expert knowledge so a program could reason its way to a solution. The excitement died down, funding dried up, the field went through long periods of disillusionment. But the expert systems, neural networks, and finally statistical machine learning kept on growing, each in its own way. Artificial Intelligence is a part of everyday life now, driving product development across industries and shaping the course of technological progress. Among the areas of human activity that have seen fundamental changes thanks to this development, quantitative investment is one of the most prominent. In particular, Deep Reinforcement Learning (DRL) is now able to make it possible to optimize a portfolio in real time and adapt it to changing conditions in the market. An illustrative example of such DRL is the work of Huang, Zhou and Song, who managed to create an actor-critic design where the reward function was based on the Sharpe ratio. After testing this model against the CSI 300 index, they found that it outperformed conventional econometric benchmarks during the period of back testing, which highlights

the model's advantage without ignoring time variability of markets.¹

Machine learning has advanced portfolio construction along a second and quite different path. Hierarchical Risk Parity (HRP), formulated by López de Prado, applies clustering methods drawn from graph theory to build diversified portfolios, and in out-of-sample testing it has outperformed classical mean–variance optimisation.² The importance of HRP for the financial community lies in its sidestepping of the covariance-matrix inversion that makes traditional optimisation so unstable in practice. The arrival of AI in wealth management, most visibly through robo-advisors, has changed personal finance by making advisory services more efficient, more accessible and more firmly grounded in data. Significant gaps nonetheless remain between the promise and the practice. Chief among them is an incomplete understanding of how AI is to be folded into a holistic wealth management strategy. The literature has grown quickly, but a large share of it isolates single components of the robo-advisory proposition, such as portfolio management, risk assessment or investment selection, without confronting the broader question of what AI does to an individual's complete financial plan.³

The wider research field encompasses robotics, speech recognition, image recognition, natural language processing and expert systems. Face recognition, voice-driven interfaces and interest-based recommendation algorithms are familiar instances. The rapid development of AI has consequences for every walk of life, and among them the financial field, or science and technology finance, has been the most profoundly affected.⁴ India provides an unusually instructive setting in which to examine these claims. The country combines a very large retail investor base, a public digital infrastructure of considerable reach, a young and mobile-first investing population, and a regulatory apparatus that has chosen to engage with AI early rather than retrospectively. What is less clear is whether the academic and professional literature, taken as a whole, supports the confident narrative that surrounds AI in Indian finance. The present paper addresses that question by reviewing the available body of work and organising its findings into a structured account of where AI is delivering value, where it is not yet doing so, and what stands in the way.

1.2 Artificial Intelligence in India's Financial Services Landscape

The Indian financial sector's engagement with AI has been shaped by three conditions that do not coexist in most markets. First, an identity and payments layer of exceptional reach has generated transaction data at a volume and granularity that supervised learning models can exploit. Second, the cost of servicing a small retail account through human advisors is prohibitive in a market where the median investible surplus is modest, which makes automation a question of viability rather than preference. Third, the regulator has moved to define the terms of AI use while adoption is still forming. Evidence on the extent of adoption comes from the surveys conducted for the Reserve Bank of India's FREE-AI Committee. The surveys found that 20.8 per cent of the entities covered were deploying AI systems at the time of the exercise, principally in customer support, sales, credit underwriting and cybersecurity, while 67 per cent expressed an interest in exploring such systems. The gap between the two figures is the most significant fact in the Indian picture: intent substantially exceeds implementation, and the barriers to closing that gap are institutional rather than technical.

On the market side, the digital advisory segment is expanding from a small base. The India robo-advisory market was valued at USD 512.31 million in 2025 and is projected to reach USD 6,993.86 million by 2034, at a compound annual growth rate of 33.03 per cent, with direct plan-based and goal-based services accounting for 54.2 per cent of the market, fintech providers for 48.6 per cent, and retail investors for 72.1 per cent of end users. The dominance of retail users and of goal-based products indicates that the Indian trajectory differs from the mass-affluent model on which much of the Western robo-advisory literature is founded.

2.1 Review of Literature

López de Prado (2016) introduced Hierarchical Risk Parity, applying hierarchical clustering to the correlation structure of assets and allocating capital recursively down the resulting tree. Because the method never inverts the covariance matrix, it avoids the instability that has long undermined mean–variance optimisation in practice. Out-of-sample testing showed superior risk-adjusted performance, and the technique has since been widely adopted in systematic asset management. **Sironi (2016)** traced the shift from product-centred distribution to goal-based investing, arguing that the significance of robo-advisory lies less in automation of allocation than in the reframing of the client conversation around life goals. The work established the conceptual vocabulary that later empirical studies of digital advice have relied upon. **Fischer and Krauss (2018)** applied long short-term memory networks to the constituents of the S&P 500 and found that the recurrent architecture outperformed random forests, deep feed-forward networks and

logistic regression in directional prediction. The study also noted that excess returns attributable to the model declined markedly in later periods, a caution relevant to any claim of durable machine-learning alpha. **Jung, Dorner, Weinhardt and Pasmaz (2018)** designed a robo-advisor specifically for risk-averse investors of limited means, and observed that acceptance depended on the transparency of the recommendation process rather than on the sophistication of the underlying allocation engine. Their finding anticipates the explainability problem that dominates the present literature. **D'Acunto, Prabhala and Rossi (2019)** examined a robo-advisory rollout using Indian brokerage account data, and produced one of the few causal studies conducted in an Indian setting. Investors who were previously under-diversified gained substantially from automated advice, improving diversification and reducing behavioural trading errors. Investors who were already well diversified gained little. The implication is that the welfare value of AI-driven advice in India is concentrated among precisely those investors who are hardest to reach commercially. **Gu, Kelly and Xiu (2020)** conducted a comparative assessment of machine-learning methods for empirical asset pricing and reported large gains over linear models, with neural networks and regression trees performing best. Their analysis identified interaction effects among predictors as the principal source of improvement, which explains why the advantage is not easily replicated by adding more linear factors. **Bartram, Branke and Motahari (2020)** surveyed the use of AI across the asset management value chain, covering security selection, portfolio construction, risk management, trading and client servicing. They concluded that the strongest returns to AI accrue in operational functions rather than in return prediction, and warned that data-mining bias and the absence of economic priors constitute the discipline's central methodological hazards. **Kavita and Verma (2025)** reviewed the prospects of robo-advisory in wealth management and observed that assets under management in robo-advisory markets were projected to reach about USD 33.49 billion by the end of 2023 and to grow at a CAGR of 14.01 per cent to roughly USD 56.58 billion by 2027, and that the rise of robo-advisors in India has been slower than in several developed countries although the trend is gaining momentum. **Reserve Bank of India (2025)** published the report of the Committee on a Framework for Responsible and Ethical Enablement of Artificial Intelligence on 13 August 2025. The committee, constituted in December 2024 and chaired by Dr Pushpak Bhattacharyya of IIT Bombay, was mandated to assess AI adoption in financial services, review global regulatory approaches, identify risks for regulated entities and recommend a governance framework suited to India, and its report sets out seven guiding principles, described as Sutras, together with 26 recommendations across six strategic pillars. The six pillars are infrastructure, policy, capacity, governance, protection and assurance, and the recommendations range from AI innovation sandboxes and indigenous financial AI models to audit, governance and incident-reporting mechanisms, with explicit attention to data privacy, algorithmic bias and cybersecurity. **Securities and Exchange Board of India (2025)** approached the same problem from the securities-market side. By notifications dated 10 February 2025, SEBI amended the Securities Contracts (Regulation) (Stock Exchanges and Clearing Corporations) Regulations, 2018 and the SEBI (Intermediaries) Regulations, 2008 to insert provisions on the responsible use of artificial intelligence. Under the amendment, any SEBI-regulated person using AI or ML tools, whether developed internally or procured from third-party technology service providers and irrespective of the scale or scenario of adoption, is solely responsible for the privacy, security and integrity of investor and stakeholder data throughout the processes involved. A consultation paper dated 20 June 2025 proposed a fuller framework to ensure accountable deployment of AI/ML models, to promote responsible innovation alongside market integrity and investor protection, and to govern the use, disclosure and audit of such systems across key market functions.

3.1 Research Methodology

Research methodology denotes the specific procedures used to locate, select, organise and evaluate material on a subject. In a review study, the methodology section performs an additional function: because the paper generates no primary observations of its own, the credibility of its conclusions rests entirely on the transparency of its selection and coding rules.

3.1.1 Research Objective

➤ To study the uses of Artificial Intelligence in generating wealth and managing individuals' finances in India by reviewing different research works, regulatory documents and industry reports.

3.1.2 Research Design

The study is descriptive cum analytical in nature, based on a systematic review of secondary literature supported by structured content analysis.

3.1.3 Hypothesis

H0: Artificial intelligence-based applications make no significant contribution to finance and wealth management outcomes in India.

H1: Artificial intelligence-based applications make a significant contribution to finance and wealth management outcomes in India.

3.1.4 Data Collection

The study relies exclusively on secondary sources. Material was drawn from peer-reviewed journals, regulatory publications of the Reserve Bank of India and the Securities and Exchange Board of India, professional research reports and reputable industry commentary. The search covered the period from January 2016 to May 2026 and used combinations of the terms artificial intelligence, machine learning, robo-advisory, wealth management, portfolio-optimisation, algorithmic finance and India.

Inclusion required that a source (a) address the application of AI or ML to a financial or wealth management function, (b) report an outcome, a framework or an empirical finding rather than mere description, and (c) be traceable to an identifiable publisher, journal or regulator. Sources were excluded where they were purely promotional, where methodology was not disclosed, or where the AI component was incidental. The protocol yielded a final corpus of **22 sources**, which constitutes the unit population for all analysis reported in Section 2.

3.1.5 Statistical Tools

Each source in the corpus was coded independently on six dimensions: thematic focus, year of publication, AI technique, functional area of wealth management, direction of reported impact and barriers identified. Descriptive tools, namely frequency distribution and percentage, were used to summarise the coded data. To test the hypothesis, a two-tailed binomial sign test was applied to the coded direction-of-impact variable, with the null expectation set at $p = 0.5$. Maturity assessments reported in Table 2.5 are the researchers' ordinal judgements derived from the coded corpus and are stated as such.

4.1 Analysis and Interpretation

In accordance with the research objective, the coded corpus has been analysed and the results are presented below. Where a table reports counts, those counts refer to the 22 sources described prior in the paper.

4.1.1 Thematic Distribution of the Reviewed Literature

Table 4.1 (A) classifies the corpus by dominant theme. Algorithmic portfolio optimisation and robo-advisory together account for 45.45 per cent of the corpus, confirming that investment management remains the centre of gravity of the field. Regulation, ethics and governance form the third largest cluster at 18.18 per cent, and the whole of that cluster is concentrated in the final two years of the review window, which reflects the very recent arrival of formal supervisory attention.

Table 4.1 (A): Thematic Distribution of Reviewed Sources				
Sr. No.	Thematic Focus	No. of Sources	Per cent	Cumulative %
1	Algorithmic and ML-based portfolio optimisation and asset pricing	5	22.73	22.73
2	Robo-advisory and digital wealth platforms	5	22.73	45.46
3	Regulation, ethics and governance of AI in finance	4	18.18	63.64
4	AI in credit assessment, lending and risk management	3	13.64	77.28
5	Financial inclusion and investor behaviour	3	13.64	90.92
6	Fraud detection, RegTech and	2	9.08	100.00

	cybersecurity			
Total		22	100.00	—

Source: Researchers' content analysis of the reviewed corpus (2016–2026)

4.1.2 Year-wise Distribution of the Reviewed Literature

Table 4.2 (A) sets out the distribution of the corpus over time. The concentration is unmistakable:

40.91 per cent of all reviewed material was published in 2025 or later. Two readings of this are possible. The generous reading is that the field has reached an inflection point at which both scholarship and regulation have matured simultaneously. The cautious reading is that much of the recent literature has not yet been exposed to replication or to a full market cycle, and its conclusions should therefore be held provisionally.

Table 4.2 (A): Year-wise Distribution of Reviewed Sources			
Year of Publication	No. of Sources	Per cent	Predominant Concern of the Period
2016	2	9.09	Foundational methods; goal-based advisory concept
2017–2018	3	13.64	Deep learning for prediction; robo-advisor design
2019	2	9.09	Early empirical evaluation; first reporting norms
2020	3	13.64	Systematic surveys; empirical asset pricing
2021–2022	2	9.09	Adoption studies; platform consolidation
2023–2024	3	13.64	Reinforcement learning; generative AI in advice
2025–2026	7	31.81	Governance frameworks; agentic and personalised AI
Total	22	100.00	—

Source: Researchers' content analysis of the reviewed corpus

4.1.3 AI Techniques and their Functional Application in Wealth Management

Table 4.3 (A) maps the principal AI techniques identified in the corpus to the wealth management functions in which they are applied. The mapping makes a point that aggregate adoption figures conceal: the techniques delivering the most reliable value in India are not the most sophisticated. Gradient boosting on structured data, an unglamorous method by current standards, supports credit and fraud functions that are already in production at scale, whereas deep reinforcement learning, which dominates the research literature, remains largely confined to institutional and experimental settings.

Table 4.3 (A): AI Techniques Mapped to Wealth Management Functions			
AI / ML Technique	Principal Function Served	Reported Advantage	Sources Citing
Supervised learning (gradient boosting, random forest)	Credit scoring, default prediction, churn	Handles non-linear interactions in structured data	8

Table 4.3 (A): AI Techniques Mapped to Wealth Management Functions

AI / ML Technique	Principal Function Served	Reported Advantage	Sources Citing
Deep neural networks and LSTM	Return forecasting, time-series signal extraction	Captures sequential dependence in price data	6
Deep reinforcement learning (actor-critic)	Dynamic portfolio allocation and rebalancing	Adapts allocation to changing market regimes	4
Hierarchical clustering (HRP and variants)	Diversified portfolio construction	Avoids covariance matrix inversion and its instability	3
Natural language processing and LLMs	Advisory chat, document processing, sentiment	Scales client interaction at negligible marginal cost	7
Anomaly detection and graph analytics	Fraud interception, AML, transaction monitoring	Identifies patterns invisible to rule-based systems	5
Recommendation and personalisation engines	Goal-based product matching, nudging	Improves engagement and contribution persistence	4

Source: Researchers' content analysis. Counts are non-exclusive; a single source may cite multiple techniques.

4.1.4 Level of Adoption of AI in the Indian Financial Sector

Table 4.4 (A) presents the adoption position reported in the surveys conducted for the RBI's FREE-AI Committee. The distribution is the clearest available statement of the Indian condition. Roughly one entity in five has deployed AI; two in three want to; the residual has neither deployed nor expressed intent. The interval between the first and second groups represents the actual size of the near-term Indian opportunity, and the reasons it has not closed are examined in Table 4.6 (A).

Table 4.4 (A): Status of AI Adoption among Surveyed Entities in India

Adoption Status	Share of Surveyed Entities (%)	Principal Areas of Deployment or Interest
Currently deploying AI systems	20.80	Customer support, sales, credit underwriting, cybersecurity
Interested in exploring AI systems	67.00	Process automation, risk analytics, personalisation

Neither deploying nor exploring (residual)	12.20	Constrained by cost, capability or regulatory caution
Total	100.00	—

Source: Compiled from the surveys reported in the RBI FREE-AI Committee Report, 13 August 2025. The residual category is derived by the researchers.

4.1.5 Maturity of AI Applications across Wealth Management Functions

Table 4.5 (A) records the researchers' ordinal assessment of maturity, on a five-point scale, for each functional area covered by the corpus. Maturity here denotes the extent to which an application has moved from research demonstration to routine production use at scale in the Indian market. The gradient is steep and its direction is consistent: functions in which the machine's output can be checked against a verifiable outcome, such as whether a transaction was fraudulent or a loan defaulted, are mature. Functions in which the output is a judgement whose correctness is revealed only over decades, such as a retirement plan, are not.

Table 4.5 (A): Assessed Maturity of AI Applications in Indian Wealth Management			
Functional Area	Maturity Score (1–5)	Stage	Basis of Assessment
Fraud detection and transaction monitoring	4.6	Mature	Production deployment across banks; verifiable ground truth
Credit scoring and underwriting	4.3	Mature	Widely operational in digital lending; strong data availability
Conversational service and query handling	4.0	Mature	NLP deployment at scale; multilingual expansion underway
Onboarding, KYC and document processing	3.9	Scaling	Supported by digital identity infrastructure
Automated portfolio allocation and rebalancing	3.2	Scaling	Growing platform coverage; largely rules-plus-ML hybrid
Goal-based robo-advisory	2.9	Emerging	Rapid growth from a small base; retail-dominated
Predictive return forecasting for retail portfolios	2.2	Emerging	Performance decay documented; limited retail deployment
Holistic life-cycle and tax-aware financial planning	1.8	Nascent	Identified as the principal gap in the literature

Source: Researchers' ordinal assessment derived from the reviewed corpus. Scores express relative maturity within this study and are not derived from a market survey.

4.1.6 Barriers to AI Adoption Identified in the Literature

Table 4.6 (A) reports the frequency with which each barrier was identified across the corpus. Counts are non-exclusive. Algorithmic opacity leads the list at 72.73 per cent, and its prominence is instructive. Opacity is not principally an engineering failure; it is a compliance and trust failure, and it is precisely the constraint that the FREE-AI framework and the SEBI amendments have been designed to address. That the three leading barriers, opacity, data

security and literacy, are all matters of governance rather than modelling capability is the central diagnostic finding of this review.

Table 4.6 (A): Frequency of Barriers Identified in the Reviewed Corpus (n = 22)

Sr. No.	Barrier	Sources Identifying	Per cent of Corpus	Nature
1	Algorithmic opacity and lack of explainability	16	72.73	Governance
2	Data privacy, security and consent management	15	68.18	Governance
3	Low financial and digital literacy among users	13	59.09	Demand-side
4	Regulatory ambiguity and unclear accountability	12	54.55	Governance
5	Model risk, overfitting and performance decay	11	50.00	Technical
6	Trust deficit and preference for human advisors	10	45.45	Demand-side
7	Algorithmic bias and risk of exclusion	9	40.91	Ethical
8	Talent scarcity and infrastructure cost	7	31.82	Supply-side

Source: Researchers' content analysis. A single source may identify more than one barrier, so percentages do not sum to 100.

4.1.7 Regulatory Evolution Governing AI in Indian Finance

Table 4.7 (A) traces the regulatory sequence. India's supervisory posture has moved from disclosure to enablement-with-accountability in roughly six years, an unusually compressed trajectory. The 2019 SEBI circular required intermediaries to declare what AI systems they used. The 2025 amendments made them answerable for what those systems do. The FREE-AI report then supplied an affirmative architecture within which such systems are expected to operate.

Table 4.7 (A): Regulatory Milestones for AI in Indian Financial Services

Date	Regulator	Instrument	Substance
4 January 2019	SEBI	Circular on AI/ML reporting	Directed recognised exchanges to establish a uniform framework for tracking AI/ML systems used by intermediaries, under the Enhanced Supervision Programme
December 2023	SEBI / Exchanges	Revised reporting timelines	Expanded scope and altered submission periodicity for AI/ML disclosures

26 December 2024	RBI	Constitution of FREE-AI Committee	Eight-member expert committee tasked with assessing adoption, reviewing global approaches, identifying risks and recommending a framework
10 February 2025	SEBI	Intermediaries (Amendment) Regulations, 2025 and related amendments	Inserted provisions on responsible use of AI; placed sole responsibility for data privacy, security and integrity on the regulated user of AI/ML tools
2 April 2025	Exchanges	Harmonised AI/ML reporting circulars	Half-yearly reporting for algorithm-using members, annual otherwise; NIL declarations mandatory
20 June 2025	SEBI	Consultation paper on AI/ML governance	Proposed framework covering safe deployment, disclosure and audit of AI/ML across key market functions
13 August 2025	RBI	FREE-AI Committee Report	Seven guiding Sutras and 26 recommendations across six pillars: infrastructure, policy, capacity, governance, protection and assurance

Source: Compiled by the researchers from SEBI and RBI publications and professional commentary thereon.

4.1.8 Growth Trajectory of the Indian Robo-Advisory Market

Table 4.8 (A) presents the reported market value for 2025 and the projected value for 2034, together with intermediate values interpolated by the researchers at the implied compound growth rate. The interpolated figures are presented to show the shape of the trajectory and should not be read as independent forecasts.

Table 4.8 (A): India Robo-Advisory Market Value, 2025 to 2034 (USD Million)		
Year	Market Value (USD Mn)	Basis
2025	512.31	Reported
2026	685	Interpolated
2027	916	Interpolated
2028	1,225	Interpolated
2029	1,637	Interpolated
2030	2,189	Interpolated
2031	2,927	Interpolated
2032	3,913	Interpolated
2033	5,232	Interpolated
2034	6,993.86	Projected (reported)

Source: End-point values as reported in industry research (CAGR of 33.03 per cent for 2026–2034); intermediate values interpolated by the researchers at the implied growth rate.

4.1.9 Testing of the Hypothesis

Each source in the corpus was coded on the direction of the impact it reported. A source was coded positive where it found that AI applications materially improved a financial or wealth management outcome, whether in returns, risk control, cost, accuracy or access. A source was coded mixed or negative where the reported benefit was absent, transient, or offset by a countervailing cost.

Table 4.9 (A): Direction of Reported Impact and Binomial Sign Test

Coded Direction	No. of Sources	Per cent
Positive and material contribution reported	19	86.36
Mixed, conditional or negative finding reported	3	13.64
Total	22	100.00

Source: Researchers' content analysis of the reviewed corpus

Table 4.9 (B): Test Statistics

Statistic	Value
Number of coded sources (n)	22
Observed positive findings (k)	19
Observed proportion	0.8636
Null expected proportion (p0)	0.5000
Exact one-tailed probability, $P(X \geq 19)$	0.000428
Exact two-tailed probability	0.000856
Significance level (α)	0.05
Decision	Reject H_0

Source: Computed by the researchers. Exact binomial probabilities; no normal approximation applied. Since the two-tailed exact probability of 0.000856 is far below the 0.05 threshold, the null hypothesis that Artificial Intelligence-based applications make no significant contribution to finance and wealth management outcomes in India is rejected, and the alternative hypothesis is accepted. The result should be read with an explicit caveat. Review corpora are exposed to publication bias, since studies reporting null results are less likely to be published, and the coded proportion is therefore an upper bound on the true proportion. What the test establishes is that the weight of available published evidence runs decisively in one direction, not that the effect size is as large as the count implies.

5.1 Findings

- Investment management dominates the literature, but not the practice.** Portfolio optimisation and robo-advisory together account for 45.46 per cent of the reviewed corpus, yet the functions actually operating at scale in India are fraud detection, credit underwriting and customer service. Research attention and commercial deployment are pointed in different directions, and the gap is itself a finding.
- Intent to adopt AI far exceeds actual deployment.** Roughly 20.8 per cent of surveyed entities were deploying AI while 67 per cent expressed interest in doing so. The 46.2 percentage-point gap is not explained by the availability of technology, which is largely commoditised, but by institutional readiness: data governance, audit capability, model risk management and skilled staff.
- Maturity tracks the verifiability of outcomes.** Applications where the model's output can be checked against an observable result within a short horizon score highest on maturity, reaching 4.6 for fraud detection and 4.3 for credit underwriting. Applications whose correctness is revealed only over many years score lowest, with holistic life-cycle planning at 1.8. This suggests that the constraint on advanced wealth applications is the feedback loop, not the algorithm.
- The binding constraints are governance rather than technical.** The three most frequently cited barriers, algorithmic opacity at 72.73 per cent, data privacy and security at 68.18 per cent, and low financial and digital literacy at 59.09 per cent, are all matters of trust, disclosure and comprehension. Model risk, a genuinely technical constraint, is cited by half the corpus and ranks fifth.

5. **Indian regulation has moved from disclosure to accountability.** The trajectory from the SEBI reporting circular of 2019 to the amendments of February 2025 and the RBI FREE-AI report of August 2025 represents a shift from asking institutions to declare their use of AI to holding them answerable for its consequences, and then to supplying an affirmative framework of seven principles and 26 recommendations within which responsible adoption is expected to occur.
6. **The Indian robo-advisory market is expanding rapidly from a small base.** A value of USD 512.31 million in 2025 projected to USD 6,993.86 million by 2034 implies a compound rate above 33 per cent, with retail investors accounting for 72.1 per cent of end users and goal-based services for 54.2 per cent of the market. The Indian profile is therefore mass-retail and goal-oriented rather than mass-affluent, which limits the transferability of Western robo-advisory research.
7. **The welfare gain from AI advice is unevenly distributed.** Causal evidence from Indian brokerage data indicates that automated advice substantially benefits investors who were previously under-diversified while adding little for those already well diversified. The investors with most to gain are also those least likely to be commercially attractive to acquire, which creates a distributional problem that market forces alone will not resolve.
8. **Machine-learning performance advantages tend to decay.** Several studies report that excess returns attributable to a model diminish in later periods as the signal is arbitrated away. Any claim of durable AI-generated alpha should therefore be treated as a claim requiring continuous re-validation rather than a settled result.
9. **Holistic financial planning remains the principal gap.** The literature addresses portfolio management, risk assessment and investment selection as separate problems and rarely examines the effect of AI on an individual's complete financial plan, encompassing insurance, taxation, liabilities, liquidity and succession. This is simultaneously the largest research gap and the largest commercial opportunity identified by the review.
10. **The evidence supports the alternative hypothesis.** With 19 of 22 sources reporting a material positive contribution and an exact two-tailed binomial probability of 0.000856, the null hypothesis is rejected at the 5 per cent level, subject to the publication-bias qualification recorded in Section 2.1.9.

6.1 Conclusion

The review concludes that Artificial Intelligence has made a measurable and statistically supported contribution to finance and wealth management in India, but that the contribution is narrower and more conditional than the prevailing commentary suggests.

Wherever outcomes are quantifiable and feedback is quick, AI is already an everyday utility: fraud is detected, credit is priced, queries are answered, documents are read. Where outcomes are slow to reveal themselves and judgement is inextricable, not least in comprehensive personal financial planning, it remains a promise. The force preventing the distance from being closed is not modelling capability. The techniques are available, the data is in abundance, and the costs of computation are falling. What limits adoption is the constellation of problems the reviewed literature most insistently identifies: a model whose reasoning cannot be explained cannot be vindicated before a regulator or a customer; data that cannot be governed cannot be safely used; and an investor who does not understand a recommendation will not act upon it, however compelling the recommendation may be.

These are institutional issues, and India's regulators have perceived them to be such. The FREE-AI framework and the SEBI amendments of 2025 should be read as the conditions under which innovation at scale can take off. For India specifically, the most crucial finding concerns distribution. The households likely to benefit most from algorithmic advisory are those currently sporting consolidated, poorly diversified and behaviourally driven portfolios, and these are households of small means in smaller metros and towns. Serving them is technologically simple and commercially unattractive. Whether AI in Indian wealth management will be a financial inclusion tool or an efficient channel for serving the already wealthy will be decided by product design, distribution economics and regulatory incentives, not by model quality. That, rather than the search for incremental predictive accuracy, is where the next decade's effort in the field should be directed.

6.2 Limitations and Scope for Further Research

The study rests entirely on secondary sources and generates no primary observations, so its conclusions reflect the state of the published literature rather than direct measurement of practice. The corpus of 22 sources, while selected under a stated protocol, is modest, and the coding of thematic focus, impact direction and maturity involves researcher judgement that another analyst might exercise differently. Publication bias, as noted, inflates the observed proportion of positive findings. English-language sources predominate, which may under-represent regional scholarship.

Four directions for further work follow. First, a primary survey of Indian retail investors measuring actual trust in and comprehension of algorithmic advice would address the demand-side barrier that this review can only observe indirectly. Second, a longitudinal study of a single robo-advisory platform's client cohort would test whether the diversification gains reported in earlier Indian work persist over a full market cycle. Third, an assessment of institutional compliance readiness against the 26 FREE-AI recommendations would quantify the implementation gap. Fourth, and most ambitiously, an evaluation of whether large language model based advisory systems can deliver genuinely holistic and tax-aware financial plans would address the gap this review identifies as the field's principal unfinished business.

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