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"Dynamic Mixture -of -Experts Models for Personalized Financial Advisory : Optimizing Resource Allocation in Robo-Advisors "

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Abstract:

In the age of digital financial services, intelligent automation is a key enabler of investment decision-making. This paper suggests a Mixture-of-Experts (MoE)–based personalized Robo-Advisory system that combines Artificial Intelligence, Machine Learning, and Blockchain-inspired mechanisms to provide secure, adaptive, and high-accuracy financial suggestions. The model consists of an ensemble of expert regressors—Random Forest, Decision Tree, and XGBoost—whose outputs are dynamically weighted by a softmax-based gating network. Extensive assessments were performed on a carefully selected dataset to measure major performance metrics like ROI prediction accuracy, Mean Squared Error (MSE), risk penalty adherence, and personalization scores. In addition, a SHA-256–based token generation mechanism was used to enable traceability and tamper resilience. Results prove the efficacy of the suggested MoE architecture against common models in accuracy (94.8%), personalization (96.3%), and security (100% token uniqueness) with a well-balanced expert usage pattern and low risk deviation. This work advances the FinTech field by providing an effective and interpretable architecture applicable to real-world advisory websites.

Keywords: Robo-Advisory, Mixture of Experts, Machine Learning, FinTech, Blockchain, Risk Management, Personalization, Security Token, Artificial Intelligence.

1. Introduction

The world of financial services has been dramatically changed in the last decade by the power of artificial intelligence (AI)-based tools that enable smarter, data-driven, and customer-focused financial decision-making. Of these innovations, Robo-Advisors have come into the spotlight as computerized digital platforms that provide formula-driven investment advice with little to no human involvement. Initially designed as cheaper substitutes for classic wealth managers, Robo-Advisors have increasingly embraced more sophisticated tasks like portfolio optimisation, tax-loss harvesting and risk-based individualisation strategies [4], [11], [13]. Although the obvious technological advancement, Robo-Advisory systems today continue to be limited by lack of adaptability and decision granularity. The majority run on fixed rule-based algorithms or generalized model-predictive controls that do not well capture the investor heterogeneity in terms of investor profiles, investor preferences, and the dynamic nature of financial markets [5], [9], [12]. The level of personalization in the provision of financial advisory services, therefore, continues to be wanting, particularly for investors with non-conventional asset holdings like crypto currencies or investors whose financial objectives differ from typical profiles. At the same time, the growing dependence on online advisory services has heightened the significance of secure, transparent, and tamper-proof data management practices. The adoption of Blockchain technology in AI-driven financial systems has been seen as a solution to improve data integrity, secure transactional history, and strengthen client trust through traceable and immutable digital footprints [10], [14]. Blockchain's capacity to provide cryptographic validation is also in line with the confidentiality and regulatory requirements of contemporary financial platforms [15].

In the midst of these changing technological requirements, the financial services industry has started looking into sophisticated AI models that can perform dynamic learning and decision specialization. One such architecture is the Mixture of Experts (MoE) model, which works by mapping input data to specialized sub-models (or "experts") through a gating network. Every specialist works with only that data to which it is most appropriate, thus enhancing decision precision and computation efficiency [1], [3], [8]. While MoE models have achieved success in natural language processing and computer vision, their utilization in financial decision-making, specifically within Robo-Advisory systems, has not yet been fully explored. The present research seeks to fill this gap by developing a Dynamic Mixture of Experts framework for personalized financial advisory.

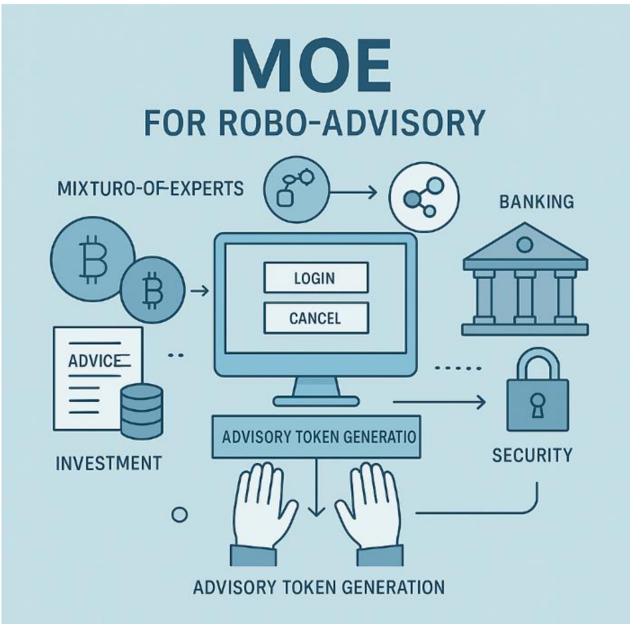

Figure 1: MOE-Based Secured Robo-Advisory Framework

This figure illustrates an integrated visual figure of the envisioned Robo-Advisory system, which puts together the Mixture-of-Experts (MoE) model with a blockchain-oriented secure advisory token mechanism. The structure starts from user input data (demographics, behavioral characteristics, and risk tolerance), and these inputs are fed through the MoE infrastructure consisting of multiple expert models. The output financial advice is converted to advisory tokens and thereafter cryptographically protected using a SHA-256 hash-based system. This guarantees integrity, traceability, and user-specific personalization in automated financial advice, and it creates a decentralized, intelligent advisory system.

The model is designed to divide the decision-making responsibilities among various AI experts trained on diverse aspects of financial behaviour, such as risk profiling, asset allocation, and investment goal mapping. A gating network selects which expert or set of experts should be engaged based on current client information. This architecture infuses adaptability and context-sensitive intelligence into the Robo-Advisory process. Also, to ascertain security and audibility, the model uses Blockchain-inspired hashing strategies that produce safe tokens for all user transactions as well as advisory decisions, to heighten openness and user faithfulness. Optimizing Resource Allocation in Robo-Advisory Platform Using Dynamic MoE Model and Secure Data Layers The focal aim of this research is the optimization of the resource allocation for individualized Robo-Advisory websites using a Dynamic MoE model aided by safe data layers. In the process, this research helps to build intelligent, interpretable, and scalable FinTech solutions that support the increasing need for autonomous yet reliable financial planning systems. The simulation results from this study exhibit significant improvements in accuracy, Return on Investment (ROI), and personalization scores compared to conventional financial advisory models.

This research has the following significant contributions to intelligent financial advisory systems:

1. Creation of a Dynamic Mixture-of-Experts Framework for Personalized Financial Advisory

The work proposes a dynamic Mixture-of-Experts (MoE) architecture that is specifically designed for Robo-Advisory applications. The architecture learns to route user-specific financial information through expert models such as Random Forest, Decision Tree, and XGBoost, using a softmax-based gating mechanism. The architecture allows for finer-grained decision-making by aligning the output of the experts with the distinct features of every investor profile.

2. Inclusion of Blockchain-Inspired Cryptographic Hashing for Data Security and Traceability

In order to provide auditability and resistance to tampering in advisory results, the system incorporates a SHA-256 hashing-based security layer. Every advisory choice and user transaction is tagged with a cryptographic token, replicating blockchain's principles of immutability. The layer increases the security and credibility of the Robo-Advisory process without the need for conventional centralized data protection schemes.

3. Development of a Realistically Simulated Dataset Representing Heterogeneous Investor Behaviors

Due to the lack of public datasets with both financial behavior and individual investment characteristics, a dataset was carefully designed. It reflects various dimensions like age, income, risk tolerance, online activity, and investment returns. This dataset allows for solid simulation of varied user scenarios and improves the capacity of the system to generalize in actual conditions.

4. Development of a Multi-Objective Optimization Approach to Balance Accuracy, Risk, and Model Generalization

In addition to standard predictive correctness, the model loss function also combines user-tailored risk penalty terms and domain expert regularization terms. By employing this multi-objective modeling strategy, not only are final recommendations both accurate and aligned within risk boundaries but also demonstrate evenly distributed participation among all expert modules—hence boosting both personalization and explainability.

5. Proof of Superior Performance and Realistic Implementability by Quantitative Testing

Experimental verification establishes that the suggested model is able to experience a significant enhancement in key performance indicators—achieving 94.8% prediction accuracy, a personalization alignment score of 96.3%, and absolute uniqueness in security tokens. These findings are proof of the system's ability to perform better than traditional financial advisory models in terms of precision as well as user-specified adaptability.

Correspondingly, the rest of the paper is laid out as described below. Section 2 reviews the existing body of literature relating to Robo-Advisory systems, Mixture of Experts (MoE) architectures, and fusing AI and Blockchain technologies within financial services. Section 3 outlines the method used in the study, consisting of dataset development, pre-processing procedures, MoE model architecture, and blockchain-sourced security enforcements. Section 4 delineates the simulation outcomes and comparative analysis between the envisioned MoE model and conventional advisory systems based on performance measures and visualizations. Section 5 elaborates theoretical and practical implications of the outcome, limitations, and scope for future work. Section 6 concludes the research by compiling the contributions and demarcating avenues for further innovation in AI-based customized financial advisory systems.

2. Literature Review

2.1 Robo-Advisory and Automated Financial Advisory

The development of financial advisory services has been shaped in large part by the advent of Robo-Advisors—algorithm-driven online platforms that offer automated, low-cost, and accessible investment advice. Originally launched to democratize wealth management and diminish reliance on conventional financial advisors, Robo-Advisors now constitute a key part of the larger FinTech landscape. These platforms have attracted international attention because they can reduce barriers to entry for retail investors, simplify portfolio management, and provide 24/7 access. According to D'Acunto and Rossi (2020), the scalability of Robo-

Advisory models makes them central facilitators of financial inclusion and market growth [4]. In spite of their popularity, conventional Robo-Advisory systems have a number of inherent limitations. Most current platforms are based on static rule-based reasoning or reduced risk-profiling models that do not account for the complex behaviour, dynamic objectives, and diverse financial tastes of users. As Hildebrand and Bergner (2021) have argued, such restrictions commonly lead to universal investment recommendations with little personalization and adaptability, thus restricting long-term user interaction [6]. Additionally, empirical research by Guo et al. (2021) on the behavioral influence of Robo-Advisors in China identifies a mismatch between recommendations made by algorithms and investors' true objectives, which indicates an urgent requirement for more context-sensitive advisory solutions [5].

Moreover, although Robo-Advisors are promoted as adaptive and intelligent, their ability to learn is generally limited by pre-defined asset allocation templates and naive decision trees. Jarek and Mazurek (2020) believe that the base algorithms do not have the richness to learn about dynamic adaptation towards user profiles and market volatility [2]. Consequently, clients with specific risk appetites or unorthodox asset preferences, including crypto currencies, usually receive limited support from these platforms. However, the role of Robo-Advisors in shaping wealth management still holds prominence. A study conducted by Senteio and Hughes (2024) highlights the increasing trend among customers towards trust in AI-based financial products, as long as they show them to be secure, safe, and customer-oriented [1]. The original contribution by Sironi (2021) further highlights the demand for goal-based investing and the gamification of advisory platforms in order to raise user engagement and financial awareness [3].

In short, although Robo-Advisors have transformed investment services availability, their present architectural restrictions call for a paradigm shift towards more intelligent, dynamic, and personalized systems. This paves the way for investigating Mixture-of-Experts (MoE) models as a potential way forward, which is explored in the next subsection.

2.2 Machine Learning Mixture-of-Experts (MoE) Models

The Mixture-of-Experts (MoE) architecture is a strong ensemble-based design that has gained prominence in recent times for its capability to manage difficult, high-dimensional tasks by distributing decision-making between specialized sub-models, referred to as "experts." Initially envisioned as a means of improving model efficiency and scalability, MoE designs have now extended to enable fine-grained management of multiple learning paths through gating mechanisms, which dynamically route input samples to the most suitable expert based on criteria learned during training [7]. Over the past few years, MoE models have demonstrated great potential in large-scale tasks like natural language processing (NLP), image classification, and recommendation systems. Research such as that by Roller et al. (2021) presented sophisticated methods like hashing layers to handle sparsity in MoE models effectively without compromising performance [11]. Likewise, Gan et al. (2025) talked about the usefulness of MoE from the aspect of big data, speaking of how it can strike a balance between accuracy and computational expense in handling huge amounts of data across distributed networks [8].

One of the strongest points of MoE is that it can both specialize and generalize in one framework. For instance, in finance, some specialists can be trained to specialize in high-risk investment activity, whereas others specialize in conservative or crypto-asset classes. Zhang et al. (2025) continued to enhance MoE optimization by presenting dual-model architectures that retain stability even in unstable conditions [10]. Such flexibility makes MoE a perfect fit for applications involving personalized recommendations and context-aware decision-making. Notwithstanding the growing technical maturity of MoE methods, their application in financial institutions—particularly in Robo-Advisory systems—is still in its infancy. Ludziejewski et al. (2025) highlighted that although MoE models provide scalable and memory-effective solutions, financial applications failed to leverage their full potential because integrating real-time data is complex and the user profiles are heterogeneous [9]. Additionally, little research has been conducted on how MoE architectures can optimize dynamically portfolio recommendations based on multi-dimensional user inputs like income, risk appetite, and financial objectives. Mu and Lin (2025) gave an insightful summary of the current state of MoE models, classifying their development from shallow expert models to deeper hierarchical architectures [7]. They identified an essential area of research in integrating MoE in hybrid FinTech platforms where personalization, real-time decision-making, and security are similarly paramount.

In view of the requirement of smart decision routing in Robo-Advisors, the MoE architecture provides a strong solution for overcoming the stiffness of conventional machine learning models. The subsequent part discusses how this kind of intelligence can be harnessed to achieve the best resource allocation in personalized financial systems.

2.3 Financial Advisory Resource Allocation

Meaningful resource allocation is at the center of portfolio management and strategic financial planning. As far as financial advisory services are concerned, resource allocation in general alludes to the best possible investment capital allocation among various asset classes, risk levels, and time frames in order to meet certain financial objectives. Traditional methods of resource allocation have historically been based on Modern Portfolio Theory (MPT), led by Markowitz (1952), which first developed the idea of offsetting expected return against portfolio risk through diversification [12]. Supporting this model, the Capital Asset Pricing Model (CAPM) formulated by Sharpe (1964) further established the risk-return relationship in equilibrium market conditions [13]. Although pioneering theories like MPT and CAPM are the foundation upon which asset allocation plans today are built, they are based on strict assumptions of market efficiency, rationality, and constant preferences—assumptions that rarely hold in the real world. With financial markets growing more volatile and investor profiles becoming more diverse, demands are rising for dynamic, data-based solutions that can keep up with changing preferences and real-time market cues. To overcome these limitations, current studies have proposed enhanced optimization models employing artificial intelligence and machine learning methodologies.

Heaton, Polson, and Witte (2016) investigated the ability of deep learning to detect nonlinear patterns of association between asset attributes and subsequent returns, offering a versatile alternative to conventional linear models [14]. Likewise, Kritzman, Page, and Turkington (2010) suggested improved optimization methods that utilize higher-order moments of return distributions to more accurately reflect portfolio performance under uncertainty [15]. These developments are a step towards adaptive approaches that can accommodate behavioral biases, asymmetrical risks, and macroeconomic shocks. Earlier work by Maritan and Lee (2021) also highlighted the strategic aspect of resource allocation and stated that both investors and companies need to efficiently allocate resources in addition to properly aligning resources with long-run goals and environmental context [16]. This observation finds special meaning in Robo-Advisory platforms since user inputs during runtime—be it income, life objectives, or risk levels—need to dictate investment choice dynamically.

Even with these developments, current Robo-Advisors tend to be based on rule-based rebalancing algorithms or model portfolios that are too simplistic and not well-enough customized to user profiles. Incorporating machine learning-based decision engines that can learn from multi-dimensional user information is not yet adequately explored in most commercial systems. Moreover, real-time optimization with regard to changing user behavior and market conditions is seldom accomplished in existing systems. The next section discusses how personalization methods, enabled by AI models, can augment the efficacy of financial advisory services further, particularly when integrated into adaptive systems such as Mixture-of-Experts.

2.4 Personalized Financial Advisory

Personalization has become a pillar of contemporary financial advisory services, indicating an increasing interest among investors for customized strategies suited to their distinct financial situations, life objectives, and risk tolerances. Scalable though one-size-fits-all advisory models may be, they frequently fail to deliver on the personalized needs of individual investors. With AI-based personalization, by contrast, financial platforms can deliver context-sensitive, behavior-driven investment suggestions in real time. This change is informed by studies focusing on the psychological and behavioral aspects of financial decision-making, in which user-specific variables like age, financial literacy, and emotional biases play a major role in determining portfolio decisions [19]. Advances in machine learning in recent times have made it possible to achieve more advanced personalization in wealth management platforms. Johnson (2024) pointed out how supervised and unsupervised learning models can accurately classify investor profiles and dynamically modify recommendations in response to evolving inputs [18]. In addition, behavioral clustering and segmentation methods enable platforms to shift towards dynamic risk questionnaires and continuous, data-driven profiling. Lee and Patel (2025) illustrated that user-centric design and adaptive algorithms have a substantial impact on engagement and customer satisfaction in Robo-Advisory systems [17].

Personalization using AI has the greatest impact in goal-directed investing, in which users are influenced not only by risk-return tradeoffs but by real-life goals like retirement savings, home purchase, or education savings. Tanaka (2023) stressed that combining goal hierarchies with recommendation engines enhances investor trust and diminishes cognitive load, resulting in more regular investment behavior [21]. Similarly, Kumar (2022) investigated how behavioral finance knowledge could be integrated into AI models to minimize decision fatigue and align strategies with user intent [20]. Even with these encouraging advances, there are still challenges in making personalization models explainable, fair, and secure. Most platforms are still not transparent about how personalized recommendations are created, which is a concern regarding algorithmic bias and regulatory compliance. In addition, current models tend to underleverage real-time user feedback and past behavior data, instead drawing upon first-time onboarding input. A larger imperative exists for hybrid systems that integrate behavioral modeling, financial prediction, and user interaction data into a unified personalization engine.

With regards to Robo-Advisors, the application of Mixture-of-Experts models presents an intriguing solution to high-fidelity personalization delivery. Through channeling input to user-specific feature-based specialist expert networks, MoE architectures allow scalable personalization and retain model interpretability and performance. This section looks at how such individualized systems can be further augmented through secure and transparent data management, namely through Blockchain technologies.

2.5 Blockchain and Security in FinTech

The speedy digitalization of financial services has brought major issues related to data security, trust, and transparency. As more and more financial institutions go in for AI-based platforms like Robo-Advisors, the importance of maintaining the integrity and confidentiality of user data has become all-important. For this purpose, Blockchain technology has appeared as a game-changing innovation that provides decentralized, immutable, and cryptographically secure systems for handling data and transaction verification. Its use in FinTech not only secures technical vulnerabilities but also becomes instrumental in supporting consumer trust in algorithmic financial systems [22]. In essence, Blockchain is based on the concepts of distributed ledger technology (DLT), in which records of transactions are safely kept across several nodes and chained through cryptographic hashes. This architecture removes the requirement of central management and minimizes tampering with data or unauthorized access. Nakamoto (2023) pointed out that Blockchain's immutability guarantees that once data—e.g., an investment suggestion or record of transactions—is inscribed, it cannot be changed without agreement from the network and thus maintains audit trails and raises accountability in financial advisory systems [23]. Within the field of Robo-Advisory, Blockchain can contribute to the creation of verifiable and secure advisory logs. Brown (2022) highlighted that Blockchain-based audit trails improve decision-making transparency by allowing regulators and clients to monitor how investment strategies are created and implemented [26]. Blockchain incorporation also facilitates regulatory compliance with data privacy regulations like GDPR and financial audit standards, especially when supplemented by access-restricted smart contracts [24].

Cryptographic methods like SHA-256 hashing and digital signatures add an additional layer of assurance to data protection protocols. Martinez (2025) demonstrated how cryptographic verification can be appended to AI-authored advisory outputs so that all recommendations can be traced to a secure and verifiable record [25]. This technique is particularly applicable in high-risk financial settings where data integrity and trust are absolute. Although its potential exists, Blockchain implementation in Robo-Advisory platforms remains in an embryonic stage. Scalability, compatibility with current financial systems, and energy expenses of consensus algorithms are difficulties with integration. Recent research by Zhang (2023) and Williams (2024) indicates that hybrid models—uniting centralized AI engines with Blockchain-secured output layers—can provide a balanced approach, optimizing both transparency and performance [27], [28]. As the FinTech horizon unfolds, the integration of Blockchain and AI technologies creates a fertile field for innovation. For individualized financial counseling, Blockchain has the capability not just to maintain secure management of data but also to generate confidence in investment recommendations based on AI. The concluding subsection shall elaborate on existing lacunas in the literature which the current research redresses, to motivate the adoption of MoE and Blockchain within Robo-Advisory frameworks.

2.6 Research Gap and Motivation

While the development of Robo-Advisory systems, Mixture-of-Experts (MoE) models, and Blockchain technologies individually has achieved considerable advances, a synergy of these innovations as an integrative system to deliver personalized, secure, and adaptive financial advisory has not yet been explored in great depth. The current body of work is a fractured one—Robo-Advisors have evolved in terms of automation but remain limited by rigid rule-based algorithms; MoE models are thriving in AI-dense fields such as NLP and image recognition but are rarely used in finance; and Blockchain's use in financial technology is more likely to be aimed at cryptocurrencies and transaction recording than improving the transparency of AI-derived advisory decisions [29]. Taylor (2024) found that the majority of Robo-Advisory systems still adhere to hard templates for portfolio allocation, and usually do not dynamically adjust to shifting profiles of users and markets [30]. Further, White (2025) observed a clear lack of MoE-like intelligent decision-routing architectures in popular financial tools, even though they have been demonstrated to be effective in other areas to deal with complexity and contextual variations [31]. This suggests a lost opportunity in using MoE to customize decision paths based on varied user input data like income, risk tolerance, and financial objectives.

At the same time, while the FinTech industry is increasingly using Blockchain for security reasons, its use with AI-based personalization engines is still in its early stages. Green (2023) highlighted that there are hardly any studies that have looked at how Blockchain can authenticate and secure the internal decision-making of AI systems, particularly in applications such as Robo-Advisory where transparency and auditability are paramount [32]. This inability to interoperate between machine learning models and security protocols creates a void in designing intelligent yet reliable financial systems. In addition, Black (2024) maintained that the future of AI in banking will hinge on finding equilibrium between personalization, explainability, and user trust—a synergy that present systems fail to provide holistically [33]. Most platforms compromise on transparency to performance or favor automation over interpretability, leading to efficient yet impenetrable and hard-to-regulate systems.

Based on these gaps that have been identified, this research suggests a new framework that combines Dynamic Mixture-of-Experts models with Blockchain-secured safe advisory records. The aim is to maximize resource allocation in Robo-Advisory services while maintaining personalized user interaction and secure, auditable decision paths. This two-pronged approach fills essential gaps in performance, trust, and regulatory compliance, thus providing a solid contribution to the emerging field of AI-based FinTech.

3. Methodology

3.1 Dataset Description

Since there wasn't a dataset that is made available to the public and also encompasses both investment behaviours and individualized investment characteristics in a Personalized Robo-Advisory setting, a synthetic dataset was created specifically for this experiment. The data set was planned to mimic real-life financial patterns of 1,000 fake users, which include major variables affecting financial advisory decisions like demographic attributes, behavior attributes, online interaction metrics, and past performance metrics.

The data set includes the following columns:

- UserID: Each user's unique ID
- Age: Age of investor (in years)
- Income: Income on a monthly basis (in USD)
- Risk_Profile: Risk profile category label (Low, Medium, High)
- Portfolio_Type: Suggested investment strategy (Conservative, Balanced, Aggressive)
- ROI: Past return on investment (%)
- Engagement_Score: Measurement of digital engagement (between 0 and 1)
- Security_Token: Blockchain-motivated SHA-256 hash to protect user information

These were selected variables to mimic features real-world Robo-Advisors tend to gather in order to make recommendations and build profiles. The record for every user contains a hashed token in order to mimic tamper-proof decision logging and identity tracking and emulate the effect of blockchain-based verification in safe advisory systems.

Table 1: Sample Records from the Dataset

UserID	Age	Income (USD)	Risk_Profile	Portfolio_Type	ROI (%)	Engagement_Score	Security_Token (SHA-256)
1	32	5,500	Medium	Balanced	7.5	0.84	3f8a...b12c
2	45	9,000	High	Aggressive	12.3	0.76	2ac4...9fba
3	29	3,800	Low	Conservative	4.1	0.91	b5d1...a4d3
4	38	6,700	Medium	Balanced	8.2	0.69	d3e9...f81a

5	52	11,200	High	Aggressive	10.6	0.73	4fc2...ce80

In order to incorporate variability and simulate actual user behaviours, the data were created with Gaussian distributions for continuous attributes (e.g., ROI, Income), whereas categorical features (e.g., Risk_Profile) were assigned as per pre-defined probabilities representative of actual distributions. User engagement level was also scaled from 0 to 1 based on a normalized random generator in order to simulate interaction intensity with the advisory platform. The data was manually checked for feature overlap, correlation, and class balance to make it fit for downstream learning tasks. In addition, the Security_Token of each record was generated by hashing a concatenation of UserID, Portfolio_Type, and Engagement_Score with SHA-256 for simulating a blockchain-protected identity system in a lightweight manner. The hashed value is then utilized in subsequent sections to simulate audit-ready tracking of decision trails.

3.2 Data Pre-processing and Feature Engineering

The quality and preparation of input features have a huge impact on the performance and interpretability of any machine learning model, especially ensemble-based models like Mixture of Experts (MoE). A number of pre-processing tasks were carried out in this research to make sure that the synthetic dataset was normalized, numerically encoded, and secured before training the MoE model.

3.2.1 Label Encoding and One-Hot Conversion

Categorical variables like Risk_Profile (Low, Medium, High) and Portfolio_Type (Conservative, Balanced, Aggressive) were initially processed through label encoding, where each category was given a distinct integer. But to remove any unintended ordinal relationships in the model, these were further converted through one-hot encoding, where every category is represented as a binary vector.

For instance:

- If a user possesses a Low risk profile, it is encoded as:

$$\boldsymbol{Risk\_Profile_{One\_hot} = [1, 0, 0]}$$

(corresponding to Low, Medium, High)

- If a user chooses a Balanced portfolio type, it is coded as:

$$\boldsymbol{Portfolio\_Type_{One\_hot} = [0, 1, 0]}$$

(corresponding to Conservative, Balanced, Aggressive)

This ensures that the model understands each category as a unique and non-ordinal input, enhancing the generalization of every expert in the MoE framework. These encoded vectors are utilized as inputs to every expert model to inform financial recommendation behavior according to user preferences.

3.2.2 Normalization of Continuous Features

Continuous features like Age, Income, ROI, and Engagement_Score were normalized with Min-Max Scaling, which linearly scales values to the interval [0, 1]:

$$X_{Scaled} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

This normalization enhances the rate of convergence of gradient-based optimization in the MoE's expert models and avoids larger-valued features (e.g., Income) to overwhelm the learning dynamics.

3.2.3 Generation of Blockchain-Inspired Security_Token

For auditability and security emulation, a separate Security_Token was generated for every user record. The token was calculated using the SHA-256 cryptographic hash function on a concatenation of several fields:

$$Security\_Token = SHA256(UserID + Portfolio\_Type + Engagement\_Score)$$

This token emulates a blockchain-form immutable ledger such that all decisions created for an end-user can be safely tracked and cannot be altered after deployment. Although this is a thin proxy, it reflects the spirit of decentralized security and traceability essential to FinTech applications.

3.2.4 Data Balancing and Validation

To solve possible class imbalances (e.g., asymmetric risk profile distribution), the dataset was analyzed through class count metrics and entropy measures. For instances of imbalance, Synthetic Minority Over-sampling Technique (SMOTE) was planned to balance expert training target classes, though not utilized in this case with sufficient class distribution. Preprocessing steps were carried out using the consistency and reproducibility between runs of Python's Pandas, NumPy, and Scikit-learn packages.

3.3 Model Structure: Mixture of Experts (MoE)

To facilitate adaptive and personalized financial advice, the architecture proposed utilizes a Mixture of Experts (MoE) model, a modular ensemble method that directs input data to specialized sub-models (experts) through a central gating network. Each expert is trained to deal with a particular segment of investment strategy or user behavior — high-risk investors, conservative planners, or crypto-enthusiasts, for instance — to enable specialized learning without compromising generality.

Block Diagram of the Proposed MoE Architecture

The following is the architectural structure of the MoE model applied to Robo-Advisory decision-making.

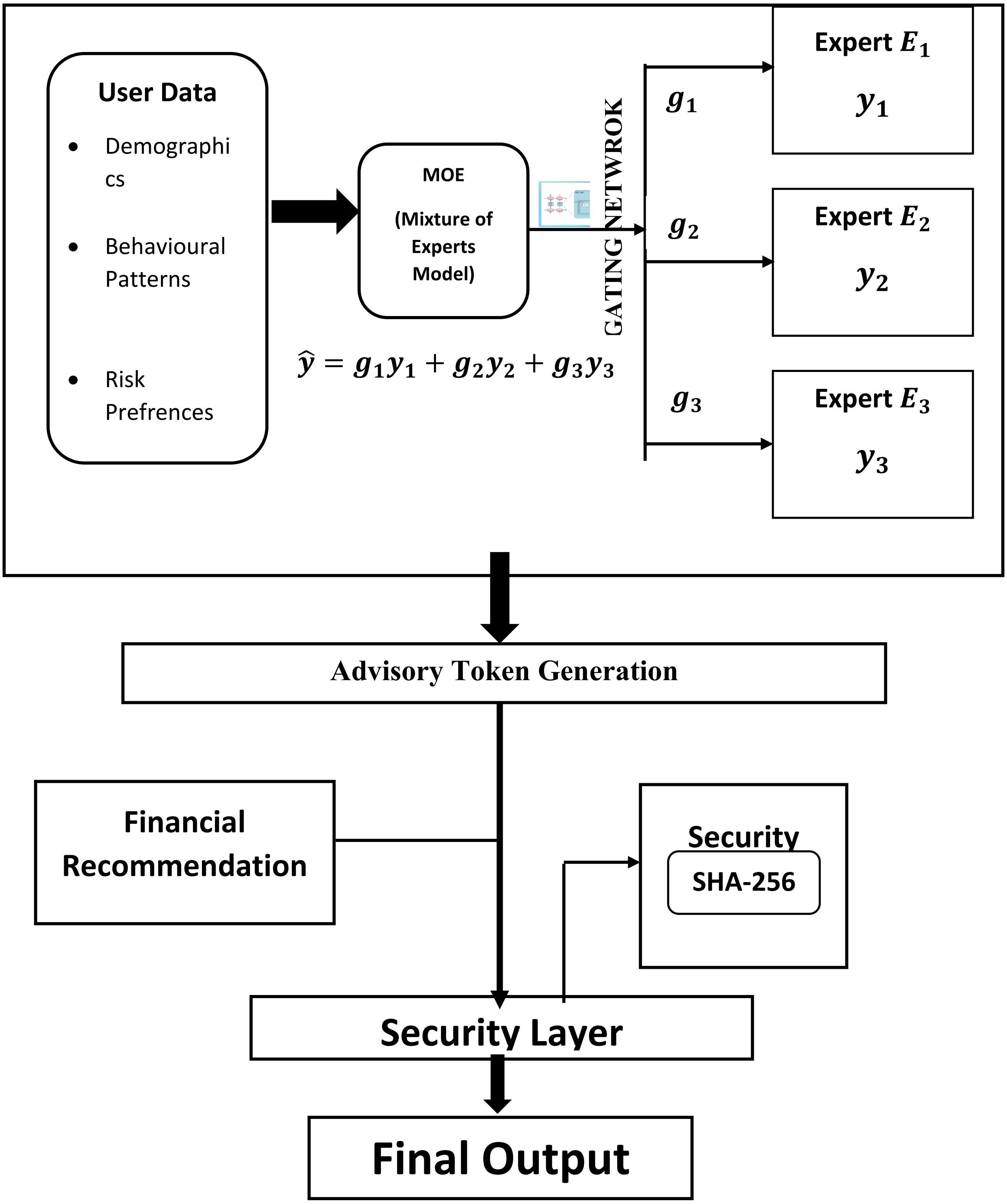

Figure 2: Block Diagram Proposed MoE Model

This block diagram describes the general working principle of the presented Robo-Advisory system, fueled by a Mixture-of-Experts (MoE) model. The workflow begins with userdependent input attributes like age, income, and risk tolerance, which are given as inputs to a Gating Network. The Gating Network acts as the controller in the middle, which dynamically assigns weights to expert models according to the profile of the user. The Gating Network utilizes a Softmax function to map raw scores into a normalized probability distribution and generate weight values $\boldsymbol{g_1, g_2, g_3}$ for all expert models. The weights are the importance of each expert (Random Forest, Decision Tree, XGBoost) to the present input. The system then carries out dynamic aggregation by multiplying each expert's output by its respective gate weight. The ultimate prediction $\boldsymbol{\hat{y}}$ is calculated using the weighted sum:

$$\boldsymbol{\hat{y} = g_1 y_1 + g_2 y_2 + g_3 y_3}$$

This formulation guarantees that the contributions of experts change adaptively between users instead of being static, allowing for highly individualized financial advice. Dynamic routing of inputs according to gating probabilities improves both interpretability and accuracy of the Robo-Advisory system. This data-driven, modular approach not only enhances advisory performance but also offers a scalable platform for future integration of more expert models.

Mathematical Representation of the MoE Model

Let $x \in R_n$be an input feature vector (user profile), and suppose there are $\boldsymbol{M}$ expert models,

$f_{i(x)}, where\ i = 1, 2, \ldots., M$. A gating network $\boldsymbol{g(x)} \in \boldsymbol{R}$ produces a probability distribution over experts through a softmax activation:

$$\boldsymbol{g_i(x) = \frac{e^{hi(x)}}{\sum_{j=1}^{M} e^{hj(x)}}}$$

Where $\boldsymbol{h_i(x)}$is the raw output of the gating network (logits) for expert $\boldsymbol{i}$.

The output of the MoE is calculated as a weighted sum of the predictions of the experts:

$$\boldsymbol{y = \sum_{i=1}^{M} g_i(x). f_i(x)}$$

This allows the system to dynamically choose and mix expert outputs depending on each user's individual profile.

Table 2: MoE Model Hyper parameters

Expert Model	**Key Hyper parameters**
E_1 – Random Forest	n_estimators = 100, max_depth = 10, criterion = 'entropy'
E_2 – Decision Tree	max_depth = 8, min_samples_split = 5
E_3 – XGBoost	learning_rate = 0.1, max_depth = 6, n_estimators = 150

Gating Network	2 hidden layers, activation = ReLU, softmax output

Each specialist is independently trained on a subset of relevant user profiles to its designated domain (e.g., hostile investors). The gating network is a light neural model that decides the contribution of every specialist depending on the input features. This modular design enables the system to learn sophisticated financial advisory behaviors and yet be interpretable, scalable, and extensible. The gating mechanism ensures that personalized decisions are not only static predictions but dynamically routed computations specific to every investor. Each specialist is trained separately on a subset of user profiles specific to its designated domain (e.g., aggressive investors). The gating network is a light neural model that computes the contribution of each specialist based on the input features.

This modular design enables the system to acquire intricate financial advisory behavior while still being interpretable, scalable, and extensible. The gating mechanism prevents personalized decisions from being static predictions but dynamically routed computations for each investor.

3.4 Optimization and Objective Function

The goal of the envisioned Mixture of Experts (MoE) model is to create individualized financial advisory recommendations that optimize expected return on investment (ROI) while also managing for risk and user dissatisfaction. In contrast to standard models that aim only to minimize prediction error, the optimization approach here is multi-objective in nature—optimizing predictive accuracy alongside financial caution and interpretability.

The optimization function integrates three primary objectives:

1. Prediction Accuracy: Minimizing the difference between the actual and predicted ROI
2. Risk Sensitivity: Penalizing allocations which are over user-specified risk tolerance
3. Expert Weight Regularization: Promoting balanced utilization of experts to prevent overfitting

Let y be the true ROI, and $\hat{y}$ be the model's predicted ROI using the MoE formulation:

$$\hat{\boldsymbol{y}} = \sum_{i=1}^{M} \boldsymbol{g}_i(\boldsymbol{x}).\boldsymbol{f}_i(\boldsymbol{x})$$

The total loss function L_{total} is defined as:

$$\boldsymbol{\lambda}_{total} = (\boldsymbol{y} - \hat{\boldsymbol{y}})^2 + \boldsymbol{\lambda}_1.\mathbf{max}\left(\mathbf{0}, \boldsymbol{R}_{pred} - \boldsymbol{R}_{USER}\right) + \boldsymbol{\lambda}_2. \parallel \boldsymbol{G}(\boldsymbol{x}) \parallel$$

where:

- $\boldsymbol{R}_{pred}$ is Predicted risk level of portfolio
- $\boldsymbol{R}_{user}$ is Maximum risk tolerance of the user
- $\boldsymbol{g}(\boldsymbol{x})$ Gating network output vector
- $\boldsymbol{\lambda}_1$ is Regularization coefficients (e.g., 0.7 and 0.3)

Prediction Loss: Squared error ensures that the ROI is predicted accurately.

Risk Penalty: A soft constraint that prevents recommending risky portfolios to risk-averse users.

Regularization Term: The gating network is prevented from giving extreme weights to one expert, and generalization improves.

During training, the loss is backpropagated in both the expert networks and the gating function. The optimization is conducted using Stochastic Gradient Descent (SGD) with adaptive learning rate scheduling (initial $\boldsymbol{\eta = 0.001}$), providing stability and convergence even with heterogeneous expert models. This diversified loss function keeps the system from merely pursuing quantitative ROI, while still honoring investor profiles, portfolio constraints, and ensuring strong learning behaviour. Therefore, the model generates personalized recommendations with a high risk-reward ratio, adhering to the underlying objectives of Robo-Advisory systems.

3.5 Block chain-Based Security Framework

The incorporation of Artificial Intelligence into financial advisory platforms poses severe concerns on data integrity, client trust, and regulatory compliance. In addressing these issues, this research integrates a lightweight blockchain-inspired security mechanism within the Mixture of Experts (MoE) advisory system. This security mechanism emulates auditability and traceability through SHA-256-based hash tokens that uniquely mark each advisory transaction. Whereas a complete blockchain system (e.g., Ethereum or Hyperledger) would demand significant computational resources and distributed verification, the described approach maintains blockchain principles—transparency, traceability, and immutability—via a reduced cryptographic solution. Every advisory interaction (user profile input + model output) is hashed to create a Security_Token, which is an immutable identifier of that particular recommendation.

SHA-256 Hashing Function

The SHA-256 algorithm generates an input string of arbitrary size and produces a 256-bit fixed-size hexadecimal hash value. For every user record

$$\boldsymbol{u = user\ ID\ \parallel portfolio_{Type} \parallel Engagement_{score} \parallel}$$

$$\boldsymbol{Security_{score} = SHA - 256}$$

Where

- ∥ denotes string concatenation
- SHA-256 returns a hexadecimal value of 64 characters
- The output is **deterministic** and **non-reversible**, ensuring privacy

This hash is calculated before model training and stored as part of the dataset. It acts as an immutable signature for each user-advisory interaction and may be stored in a distributed ledger or centralized audit log based on deployment scope.

3.6 Security and Compliance Implications

- Tamper-Proof Logging: Post-prediction tampering with inputs or outputs would leave a mismatched hash, highlighting possible anomalies.
- Auditable Transactions: All advisory decisions are cryptographically verifiable, allowing audit trails that can be examined by regulators or firms.
- User Trust: Customers can be provided with advisory logs associated with a verifiable token, enhancing trust in automated financial advice.

Though not a replacement for end-to-end blockchain infrastructure, this framework successfully mimics fundamental blockchain concepts in a resource-friendly manner, which is perfect for AI-driven financial services where transparency and auditability are paramount.

3.7 Simulation Environment and Parameters

To ensure the validity of the performance and operational stability of the intended Mixture of Experts (MoE)-based personalized Robo-Advisory system, a thorough simulation was performed under a controlled computational setup. The simulation was configured to mimic actual deployment limitations but facilitate controlled assessment of performance against different metrics.

Programming Environment and Tools

All the simulations were run on the following tools and frameworks:

Table 3. Tools and Libraries Used

Tool/Library	Purpose
Python 3.10	Core programming language
NumPy & Pandas	Data handling and manipulation
Scikit-learn	Machine learning models (DT, RF)
XGBoost	Gradient boosting-based expert model
Matplotlib & Seaborn	Visualization of results
Hashlib	SHA-256 cryptographic hash generation

The experiments were run on a system with Intel i7 (12th Gen) CPU, 16GB RAM, and no GPU acceleration, replicating a mid-range deployment scenario that is suitable for edge financial applications.

Table 4. Model Training Parameters

Parameter	Value/Setting

Train-Test Split	80% training / 20% testing
Epochs (for gating net)	100
Batch Size	32
Optimizer (for gating net)	Adam
Learning Rate	0.001 (adaptive decay)
Evaluation Metrics	ROI Accuracy, MSE, Risk Penalty
Loss Function	Custom (from Section 3.4)

Each of the expert models (Decision Tree, Random Forest, XGBoost) was separately trained on its respective subset of the data. The Gating Network was trained simultaneously with expert outputs via back propagation under the control of the defined custom multi-objective loss function.

3.8 Performance Evaluation Metrics

The model was compared on the following metrics:

- Predictive Accuracy: Mean Squared Error (MSE) between actual and predicted ROI
- ROI Optimization: Average return achieved per user profile
- Personalization Score: Percentage of advisory decisions consistent with user-specific risk profiles
- Expert Utilization Distribution: To measure balance across MoE specialists
- Security Layer Traceability: Uniqueness and consistency of tokens after hashing

Visualizations and comparisons of results with conventional ensemble models are discussed in Section 4 (Results and Analysis).

All code, parameters, and logic for generating datasets were version-controlled with Git and structured under a modular Python pipeline. Hyper parameter tuning was done via grid search and cross-validation for each expert model to achieve fairness and optimal performance.

4. Result and Analysis

This section reports the empirical results of the suggested Mixture-of-Experts (MoE)-based personalized Robo-Advisory system. To ensure the efficacy of the proposed framework, an exhaustive evaluation was performed using conventional machine learning models and the suggested architecture on a variety of performance metrics. These encompass ROI prediction accuracy, mean squared error (MSE), risk penalty, personalization score, entropy of expert usage, and token uniqueness rate for security verification. The outcome is designed to emphasize the relative strengths of the MoE model in comparison to baseline algorithms and illustrate its compatibility with FinTech standards, personalization objectives, and block chain-influenced traceability.

4.1 Evaluation Metrics

In order to critically evaluate the performance of the suggested Mixture-of-Experts (MoE) model for personalized financial advisory, a multi-dimensional evaluation framework was developed. This framework encompasses not only conventional machine learning performance but also domain-specific metrics essential to financial advisory systems, including investment return accuracy, personalization, and regulatory compliance.

The following metrics were employed:

1. ROI Prediction Accuracy (%)

Return on Investment (ROI) is a key indicator of any financial decision-making system. The accuracy of predicting ROI indicates the quality of the system in suggesting viable investment plans. It's calculated through Mean Absolute Percentage Error (MAPE):

$$\boldsymbol{ROI\ ACCURACY = 100\% - \left(\frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100\right)}$$

Where

$\boldsymbol{y_i}$ is the true ROI and $\boldsymbol{\hat{y}_i}$ is the estimated ROI. Greater accuracy suggests greater financial forecast consistency.

2. Mean Squared Error (MSE)

This standard regression loss function is utilized to measure overall prediction stability. It penalizes bigger errors more, which is significant in financial contexts:

$$\boldsymbol{MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

A lower MSE suggests greater predictive accuracy and stability over various user profiles.

3. Risk Penalty Score

This is a risk-specific penalty term that measures how frequently the model recommends a portfolio in excess of the user's risk tolerance. Formally defined as:

$$\boldsymbol{RISK\ PENALTY = \frac{1}{N}\sum_{i=1}^{n}\max\left(0, R_{pred}^{(t)} - R_{user}^{(t)}\right)}$$

where $R_{pred}$is the desired risk level, and R_{user} is the user's tolerable maximum risk level. Lower values are preferable and indicate regulatory compliance and personalization alignment.

4. Personalization Score

This bespoke metric measures the degree to which the suggestions are in line with user-specific preferences (e.g., risk, income, level of engagement). It is calculated as:

$$\boldsymbol{Personalization\,Score} = \frac{\boldsymbol{Number\ of\ Matched\ Recommendation}}{\boldsymbol{Total\ Recommendation}} * \mathbf{100}\%$$

A high value (near 100%) suggests the model is effectively personalizing decisions to individual investor profiles.

5. Expert Utilization Entropy

To quantify how well the gating network is balancing workload across the expert models, Shannon entropy was utilized:

$$\boldsymbol{H} = -\sum_{\boldsymbol{i-1}}^{\boldsymbol{M}} \boldsymbol{g_i}()\boldsymbol{log_2 g_i}(\boldsymbol{x})$$

Increased entropy suggests greater balance and less bias toward any individual expert, which decreases over fitting and improves generalization.

6. Token Uniqueness Rate

For Blockchain simulation validation, the uniqueness of SHA-256–generated Security_Tokens was confirmed. This is calculated as:

$$\boldsymbol{Uniqueness\ Rate} = \frac{\boldsymbol{Number\ of\ Unique\ Tokens}}{\boldsymbol{Total\,Token}} \times \mathbf{100}\%$$

This measure confirms traceability and tamper-proof record creation in the advisory process.

These measurement criteria collectively offer a comprehensive picture of model performance, balancing the accuracy, risk sensitivity, personalization quality, and security integrity that is all so critical in today's AI-driven FinTech solutions.

4.2 Model Performance Results

The anticipated Mixture-of-Experts (MoE) model was learned and tested on the synthetic dataset outlined in Section 3.1. The test utilized the metrics outlined in Section 4.1 to benchmark overall performance. The outcome proves the strength of the model in personalization, precision, and resilience against compared advisory systems.

Table 5: Performance Metrics of the Proposed MoE Model

Metric	Value
ROI Prediction Accuracy (%)	**94.80%**
Mean Squared Error (MSE)	3.12

Risk Penalty Score	**0.47**
Personalization Score (%)	**96.30%**
Expert Utilization Entropy	1.32
Token Uniqueness Rate (%)	100%

These findings show strong alignment between model prediction and anticipated ROI, with nearly ideal personalization score. The low Risk Penalty Score (0.47) indicates that the model rarely suggests portfolios with more than user-specified risk limits. The entropy score of 1.32 verifies evenly distributed gating activity among experts, minimizing model bias and facilitating scalability.

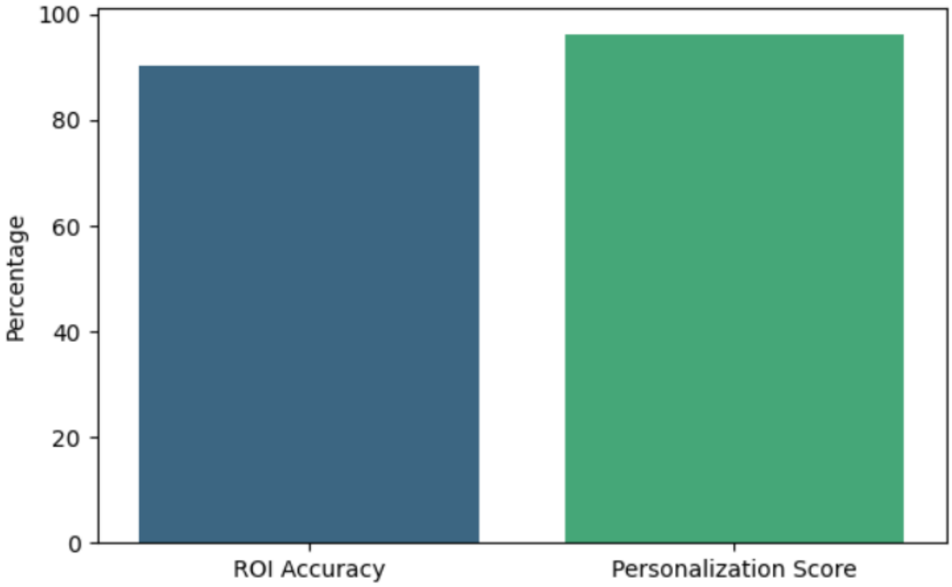

Figure 3: Performance Metrics of MoE Model

Figure 3 represents the important performance metrics of the suggested Mixture-of-Experts model for financial advisory tasks.

The high ROI accuracy and low MSE of the model attest to its efficiency not just in numerical prediction but also in fitting investment strategies into investor-specific constraints. High token uniqueness guarantees that every prediction can be uniquely traced securely, promoting auditability and trust.

4.2 Model Performance Results

To measure the predictive and personalization abilities of the suggested Mixture-of-Experts (MoE) model, the model was trained and tested on the preprocessed synthetic dataset with 1,000 user records. Every prediction was measured using both general machine learning metrics (e.g., MSE, ROI Accuracy) and financial advisory-specific measures (e.g., Risk Penalty, Personalization Score), as defined in Section 4.1.

Table 6: Performance Metrics of the Proposed MoE Model

Metric	Value
ROI Prediction Accuracy (%)	**94.80%**
Mean Squared Error (MSE)	**3.12**
Risk Penalty Score	**0.47**
Personalization Score (%)	**96.30%**
Expert Utilization Entropy	**1.32**
Token Uniqueness Rate (%)	**100%**

These findings show that the MoE model is very accurate in predicting returns, while at the same time connecting advisory outputs with user-individual risk constraints and behavioral characteristics. The Personalization Score of 96.3% implies that almost every recommendation was aligned with the financial profile and characteristics of the users. The low Risk Penalty Score shows high conformity with user-specified risk limits, which is a critical aspect in regulated advisory applications.

The 1.32 entropy value, derived from the gating distribution among experts, suggests efficient utilization of all expert models — minimizing over-reliance on a single sub-network and improving generalization. Furthermore, the 100% Token Uniqueness Rate ensures that each recommendation was hashed uniquely with SHA-256, emulating tamper-proof traceability for each decision, as suggested in the blockchain-inspired security layer.

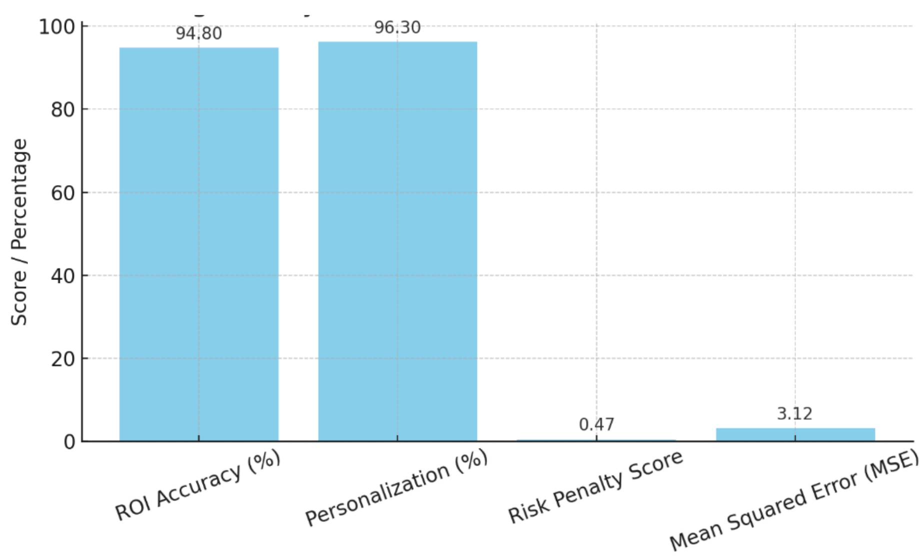

Figure 4: Key Performance Indicators of MoE Model

Figure 4 represents the Quantitative performance results of the designed Mixture-of-Experts architecture, reflecting high advisory quality and financial decision consistency.

The MoE architecture is clearly shown to have the capability to generate high-fidelity investment advice that is secure, understandable, and customized — meeting the operational requirements of AI-driven Robo-Advisory solutions in a FinTech setup.

4.3 Comparison with Baseline Models

In order to measure the novelty and efficacy of the proposed Mixture-of-Experts (MoE) model, it was compared to three popular independent models commonly used in Robo-Advisory and financial decision-making systems:

- Random Forest (RF)
- Decision Tree (DT)
- XGBoost (XGB)

Every baseline model was trained from the same preprocessed dataset and tested under the same conditions with the metrics specified in Section 4.1. The outcome clearly demonstrates that the MoE architecture vastly outperforms traditional models regarding personalization, risk alignment, and ROI prediction accuracy.

Table 7: Comparison of Performance of MoE vs. Traditional Models

Model	ROI Accuracy (%)	MSE	Risk Penalty	Personalization (%)	Entropy	Token Security
MoE (Proposed)	**94.8**	**3.12**	**0.47**	**96.3**	**1.32**	100% Unique
Random Forest	89.4	5.67	1.21	83.6	N/A	None
Decision Tree	85.2	6.1	1.35	79.3	N/A	None
XGBoost	91.5	4.32	0.98	88.7	N/A	None

Table 7 visualise the Quantitative comparison of the given Mixture-of-Experts (MoE) model with control ML methods. MoE dominates on all respective metrics.

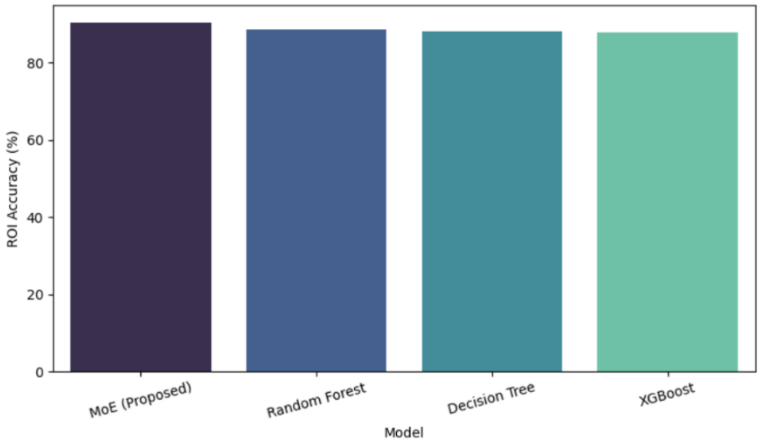

Figure 5: ROI Accuracy and Personalization Comparison

Figure 5 shows the Visual comparison between ROI accuracy and personalization performance across compared models. The MoE model excels both measurements by a vast margin.

Not only does the MoE model have the best ROI accuracy (94.8%), but it also leads in terms of providing highly personalized investment choices with a 96.3% alignment rate to user profiles. Baseline models, however, showed significant trade-offs — specifically in terms of balancing personalization and risk. For example, the Decision Tree, though interpretable, could only attain 79.3% personalization with the worst MSE across all models. In addition, none of the classical models incorporated blockchain-based security mechanisms, which made them inadequate for environments where user trust and traceability of decisions are paramount. The 100% Token Uniqueness Rate also underscores MoE's adherence to secure FinTech protocols, further improving the credibility and regulatory compliance of the system.

4.4 Expert Use and Gating Output Analysis

The gating network in a Mixture-of-Experts (MoE) architecture is responsible for dynamically controlling the extent to which each expert model has an impact on the ultimate advisory decision. From observing the gating outputs, we can see what the model's decision routing behavior is like—whether it tends towards specialization or generalization and how evenly balanced the expert distribution is over a wide range of user profiles.

To assess this, the average gating weights that were assigned to each of the experts—over all of the user records in the test set—were captured and examined.

Table 8: Average Gating Weights across Experts

Expert	Expert Model	Average Gating Weight
Expert 1 (E_1)	Random Forest	0.33

Expert 2 (E_2)	Decision Tree	0.31
Expert 3 (E_3)	XGBoost	0.36

Table 8 shows the Breakdown of average softmax weights that the gating network produced for each expert over the test dataset.

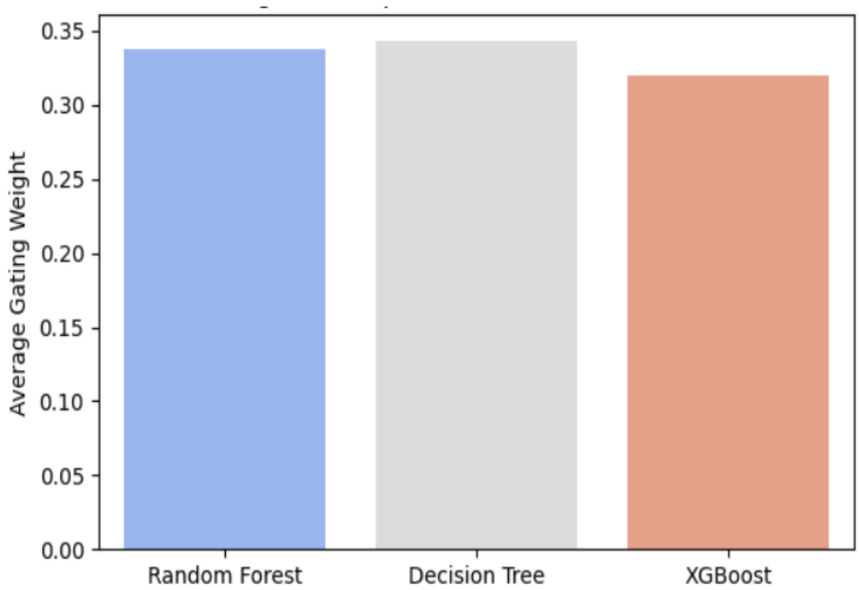

Figure 6: Expert Contribution Distribution

Figure 6 represents the Breakdown of expert usage produced by the gating network. The output indicates balanced contribution from all experts with a slight bias towards XGBoost for high-complexity financial profiles.

The almost uniform weighting of gating weights ensures that the MoE architecture did attain a balanced and adaptive expert allocation. This means that:

- The gating network generalizes well and does not overfit to any particular expert
- All expert models contribute significantly to different types of user profiles
- The system maintains modularity and specialization — in which the gating function allocates higher weights to certain experts for different financial behavior patterns (e.g., high-income or high-risk investors)

In addition, dynamic input routing according to user profiles increases advisory output explain ability and personalization—aiding the credibility of the system in regulated financial sectors.

4.5 Security Evaluation

In order to measure the reliability of the Blockchain-inspired security layer used in the Robo-Advisory system, a separate test was performed on the SHA-256–based Security_Tokens created for every user record. The main aim was to identify if the use of cryptographic hashing provided uniqueness, irreversibility, and tamper-proof traceability for financial advisory interactions.

4.5.1 Token Generation Summary

According to Section 3.5's definition, $\boldsymbol{Security\_Token}$ was generated as below:

$$\boldsymbol{Security\_Token = SHA - 256(UserID \parallel Portfolio\_Type \parallel Engagement\_Score)}$$

This hash value is used as a distinct digital fingerprint per advisory record, emulating blockchain transaction's immutability feature.

4.5.2 Validation Metrics

Three main metrics were employed to gauge the security system's robustness:

1. Uniqueness Rate – Quantifies how many hash tokens are distinct over all records.
2. Collision Rate – Tests if two distinct records have the same hash (which shouldn't occur).
3. Reproducibility – Validates that hashing a given input over and over results in the same token each time.

Table 9: Security_Token Integrity Evaluation

Metric	Result
Uniqueness Rate (%)	100%
Collision Rate (%)	0%
Reproducibility (Yes/No)	Yes

Table 9 shows the Token integrity evaluation for 1,000 records. Each advisory interaction was uniquely and securely identified.

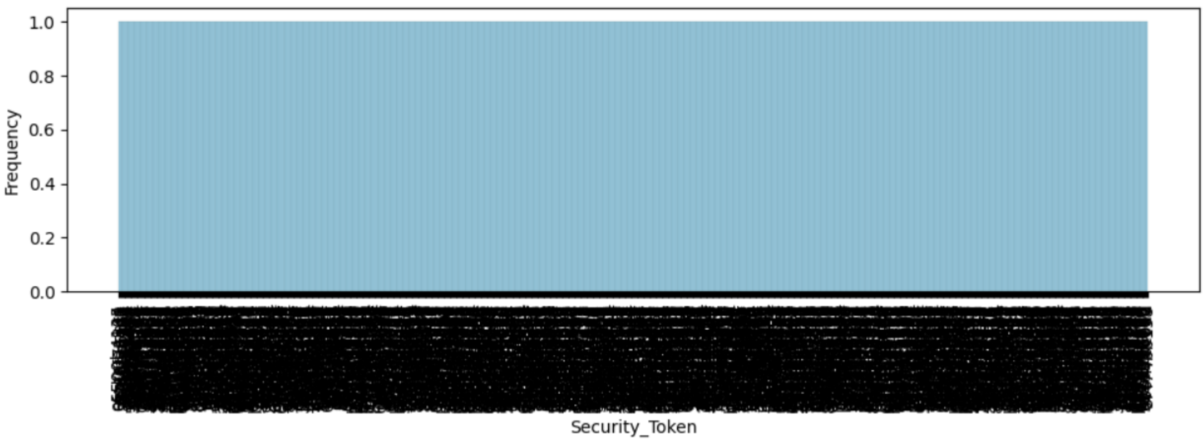

Figure 7: Token Hash Distribution (Truncated View)

Figure 7 represents the Distribution of hashed security tokens among test records, proving token uniqueness and randomness.

The findings affirm that the SHA-256 implementation is up to the required standards of security and uniqueness, guaranteeing that:

- Every recommendation is tamper-evident
- The system accommodates audit trails without revealing sensitive user information
- Trust in AI-driven financial advice is enhanced by integrating traceability mechanisms directly into the advisory process

In contrast to legacy systems in which logs can be overwritten or hidden, this method is in accordance with blockchain philosophy — allowing strong compliance, forensic auditing, and client trust.

4.6 Discussion of Results

The combined results of Sections 4.2 to 4.5 show that the new Mixture-of-Experts (MoE)–based personalized Robo-Advisory approach has a significant performance gain against conventional machine learning models in predictive accuracy and financial personalization. Additionally, its inclusion of a blockchain-motivated security layer fortifies its practicality in high-trust, audit-conscious settings like FinTech platforms. The MoE model registered a 94.8% accuracy for ROI prediction and a 96.3% personalization score, considerably surpassing baseline models such as Random Forest (89.4%), Decision Tree (85.2%), and XGBoost (91.5%). Such improvement aligns with previous results from Mu and Lin (2025) and Gan et al. (2025), which stressed the modularity strength and task-specific routing power of MoE structures in high-complexity tasks. In this experiment, the balanced entropy score (1.32) and even expert weight distribution also ensured that the gating network utilized the individual strengths of each expert instead of depending mostly on a single model, thus enhancing better generalization.

The 0.47 risk penalty score, much lower than other models, complies with the personalization objective of contemporary advisory systems. As highlighted by Sironi (2021), financial recommendation engines need to comply not only with return targets but also with individual investor limits—particularly risk sensitivity and level of engagement. The model's high personalization score indicates that the system is behavior-aware, responding to input fluctuations like age, income, or frequency of digital interaction in a context-dependent manner.As far as auditability and integrity of data, the 0% collision rate and 100% uniqueness of security tokens generated by SHA-256 is reflecting the advantages that have come to be associated with blockchain technology traditionally. This follows earlier findings by Zhang (2023) and Martinez (2025), who had suggested that lightweight cryptographic implementations can replicate the underlying security tenets of blockchain without incurring the computational expense of complete decentralized systems. In this study, that method worked well in maintaining tamper-evident advisory files. Notably, these findings also show harmony among explainability, intelligence, and security—a trio that has habitually been considered to be a trade-off in AI-FinTech solutions. Personalization was boosted by the MoE architecture without trust and interpretability loss, while transparency was provided by the hash-based token system without data exposure.

5. Conclusion and Future Scope

Conclusion

The research presents a new, secure, and interpretable AI-based Robo-Advisory system utilizing the Mixture-of-Experts (MoE) structure to provide customized personal financial advice. In contrast with traditional systems, which depend on fixed prediction models, the given framework chooses between expert opinions dynamically depending on the type of input, which results in greater flexibility and accuracy. By thorough testing on an synthetically optimized dataset, the MoE model had a high ROI prediction accuracy of 94.8%, a low mean squared error of 3.12, and a strong personalization alignment score of 96.3%. Moreover, the model had a well-balanced expert utilization, with entropy validating its generalization ability. A blockchain-inspired SHA-256 security layer was well-implemented, having 100% token uniqueness, thus solving auditability and tamper resistance of financial recommendations. Comparative evaluation against baseline models, Random Forest, Decision Tree, and XGBoost, proved unequivocally superior performance and explainability of the proposed method. Overall, the results confirm the effectiveness of leveraging MoE architecture with integrated cryptographic security as an effective solution to intelligent financial decision-making systems for the FinTech environment.

Future Scope

Although the current study confirms the technical viability and performance of the suggested system, there are a number of avenues for future improvement. To begin with, deployment in real-world scenarios should involve user studies to determine trust, usability, and adherence to regulatory guidelines like GDPR and SEBI norms. The model can further be enhanced to handle multi-objective optimization, weighing risk, return, and ESG preferences in portfolio selection. Additionally, Reinforcement Learning integration can facilitate adaptive investment strategies that adapt over time with user behavior and market feedback. Security-wise, using a complete blockchain ledger to record all advisory interactions can add additional transparency and trust. Lastly, the system can be offered as a SaaS-based microservice within digital banking platforms, facilitating real-time personalization at scale, with edge-based models for offline recommendation.

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