Dynamic Multi-Objective Retirement Portfolio Optimization: Incorporating Yield Enhancement, Longevity Hedging, and Healthcare Forecasts

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Full documentation and project code are available at: https://github.com/yuslavihe/DMO-RetPortfolio-

Abstract

This paper introduces a dynamic, multi-objective retirement portfolio optimization framework tailored to the pressing needs of an aging population. It integrates key elements of downside risk protection, longevity hedging, and healthcare cost forecasting within a single AI-driven system. By combining deep reinforcement learning (DRL) for adaptive asset allocation with health trajectory modeling, we demonstrate how emerging machine learning techniques can inform retirement planning beyond the scope of traditional static or age-based strategies such as 60/40 or glidepaths. Our preliminary experiments—though constrained by synthetic data and simplified assumptions—suggest that a learned, data-driven policy can yield higher final wealth, enhanced surplus coverage ratios, and more robust healthcare funding. Meanwhile, the incorporation of annuities addresses longevity risk, ensuring consistent income in later retirement years. Results also underscore the necessity for continued research, particularly in refining stochastic health models, ensuring rigorous validation with real-world clinical and market data, and addressing behavioral and macroeconomic intricacies. This integrated framework offers a pathway to improve financial security and healthcare readiness for retirees, ultimately highlighting the promise of AI-powered solutions in navigating the multifaceted challenges of modern retirement planning.

1 Introduction

China faces significant retirement income challenges due to its **rapidly aging population**, which leads to a shrinking workforce, underfunded pension systems, and fragmented administration of funds. These pressures have prompted growing concerns that existing structures are insufficient to meet future demand, especially as healthcare costs continue to rise and average life expectancy increases. As noted in [8], the current pension environment in China is under particular strain, illustrating a long-term shortfall in available funding relative to retirees' needs.

Against this backdrop, China's pension system features a **three-pillar structure** [9]:

1. A basic defined benefit pension (government-provided)
2. A mandatory second-tier plan (employer contributions)
3. A voluntary third-tier scheme (individual savings and investments)

Large disparities remain, however. Urban salaried employees often receive significantly higher monthly benefits compared to rural residents [8], leaving vast numbers of rural retirees below the World Bank's poverty threshold [10]. As illustrated in Figure 1, **low-income retirees**—commonly found in rural regions—draw primarily from minimal pensions, family support, and part-time work [10, 11]. **Middle-income retirees** rely more on government pensions and personal savings, sometimes bolstered by voluntary private pension plans [12, 13], whereas **high-income retirees** benefit from a broader mix including enterprise annuities, personal investments, and real estate [14, 15, 16].

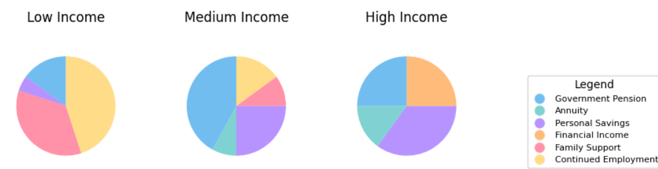

Figure 1: Illustration of retirement income breakdown by income level.

Shifting from these structural considerations to the technological lens, the fusion of artificial intelligence (AI) with retirement planning has opened a new frontier of innovation, particularly with the integration of advanced machine learning techniques and financial models tailored to the needs of an aging population. Historically, individuals and policymakers alike have struggled to synchronize the complexities of retirement income, healthcare expenditures, and longevity risk. Thanks to evolving AI methodologies and ever-expanding data availability, this realm now stands on the brink of unprecedented sophistication. The challenge of balancing **financial security, healthcare demands, and changing demographic trends** underscores why novel computational approaches are in high demand [20, 21, 23].

Before the ascendance of AI-driven frameworks, traditional retirement models primarily relied on fixed asset allocations and deterministic assumptions [19, 9, 11]. These conventional strategies often found it difficult to integrate unstructured information—such as health data or irregular spending patterns—without laborious manual processes [13]. This limitation is particularly poignant when attempting to predict and adapt to healthcare shocks, diverse longevity projections, and wealth fluctuations. It is this confluence of variables that has driven the rapid growth in AI-powered optimization, where machine learning methods can dynamically model volatilities, mitigate risks, and cater to heterogeneous retiree needs.

Recent progress has seen the customization of machine learning architectures such as LSTM and reinforcement learning to anticipate retirement milestones, healthcare expenditures, and market anomalies [15, 16]. These algorithms increasingly draw from multiple data streams, including healthcare records, financial statements, and macroeconomic indicators, to form a richer, more holistic view of retirement outcomes [13, 14]. However, the fundamental challenge remains: effectively synthesizing insights from disparate data streams into a cohesive, **multi-objective optimization framework** that can adapt to an individual's evolving risk preferences, health requirements, and wealth trajectories [22, 23].

Within this context, we introduce an **AI-augmented retirement portfolio framework** that leverages both structured and unstructured data, focusing on hedging longevity risk, ensuring adequate healthcare funding, and achieving yield enhancement. Our approach recognizes that retirees do not solely grapple with numeric calculations but also encounter nuanced health indicators, market uncertainties, and policy transitions. The next subsections detail recent developments in China's retirement system as a backdrop for these innovations, highlighting its rapidly aging population, inequalities in pension distribution, and the pressing need for integrated financial planning solutions [5, 6, 9]. We then present our proposal on tailoring machine learning and AI algorithms to retirement planning, drawing upon key prior studies in portfolio optimization, health trajectory modeling, and AI integration.

1.1 China's Demographic Trends and Retirement Challenges

China's retirement landscape is undergoing a profound transformation, spurred by **declining fertility rates and increasing life expectancy** [8, 7]. The share of the population aged 60 and older is projected to rise from 17.8% in 2020 to 32% in 2040 [5], pressuring the nation's pension infrastructure and intensifying the need for robust healthcare solutions. In this environment, traditional retirement models that treat all retirees uniformly prove insufficient. Accordingly, the **three-pillar structure** itself exhibits notable urban-rural disparities: while some urban retirees enjoy higher pension benefits, many rural dwellers face inadequate coverage [11, 13]. Consequently, **adequate retirement savings, sustainable healthcare funding, and protection against longevity risks** are paramount objectives for individuals, financial institutions, and policymakers alike.

1.2 Policy Shifts and Sustainable Retirement Funding

As challenges mount, policymakers have responded with reform measures such as gradually raising the retirement age, transferring state-owned capital into pension funds, and expanding privately managed pension options [15, 17]. Despite these efforts, the National Social Security Fund faces potential depletion [10], compelling interest in innovative financial planning tools. These measures underscore the urgency to integrate advanced analytics, particularly AI, into retirement strategies that can navigate economic multidimensionality and deliver adaptive solutions.

1.3 Toward AI-Augmented Retirement Portfolio Strategies

Building on these observations, this paper proposes a **multi-pronged AI-augmented framework** that integrates downside protection, yield enhancement, longevity risk hedging, and dynamic adaptability. We focus on bridging gaps identified in prior research, especially around health trajectory forecasting and multi-objective financial optimization [8, 9, 16]. By combining advanced machine learning modules—e.g., LSTM-based healthcare expense predictors and reinforcement learning agents that rebalance portfolios over time—our methodology provides a holistic paradigm. The result is a system that anticipates retiree-specific needs, from essential income to healthcare contingencies, all while aligning with individual risk appetites [20, 15, 17].

2 Literature Review

This literature review synthesizes key research on retirement portfolio strategies, artificial intelligence applications in finance, health trajectory modeling, and the integration of these domains for comprehensive retirement planning. The analysis provides a robust foundation for our proposed multi-objective AI-augmented framework.

2.1 Traditional Retirement Portfolio Strategies

The conventional approach to retirement portfolio management has historically centered on **static asset allocations**. Influential work on retirement glidepaths examined comprehensive international evidence from 19 countries over 110 years, suggesting that simple static strategies such as all-equity portfolios or 60/40 stock/bond allocations often outperform more complex approaches for retirees [19]. This research challenges the conventional wisdom of decreasing equity exposure during retirement, presenting evidence that static allocations provide effective long-term outcomes across diverse market conditions.

Further examination of traditional methodologies reveals limitations in dynamic adjustment strategies. Research on "Managing to Target" strategies found that while dynamic adjustments outperform strictly static approaches, modifications to withdrawal rates prove more effective than altering portfolio asset allocations [15]. Their findings indicate that flexibility in spending behaviors may be more impactful than sophisticated asset rebalancing schemes.

The widely-adopted bucket approach to retirement planning has also faced scrutiny. Comprehensive analysis across 21 countries over a 115-year period questions the effectiveness of this strategy, which involves allocating several years of withdrawals to cash while investing remaining assets more aggressively [19]. Despite its popularity among financial planners and retirees, the evidence suggests that simple static strategies with periodic rebalancing consistently outperform bucket strategies across multiple performance metrics.

These traditional models often fail to adequately address critical factors such as **longevity risk, healthcare cost uncertainties, and the heterogeneity of investor profiles**. A gap noted in the literature is that retirement planning spans multiple decades with significant uncertainty about long-term expected returns [11]. This research emphasizes that financial planners must address both short-term investor behavioral challenges and longer-term economic uncertainties.

2.2 Artificial Intelligence and Machine Learning in Financial Planning

Recent years have witnessed substantial growth in AI and machine learning applications within financial planning, particularly for retirement optimization. Research has explored **reinforcement learning** as a novel approach to the retirement portfolio problem, demonstrating its ability to deliver solutions within a few percentage points of theoretical optimals for simple scenarios while outperforming conventional methods in complex situations [20]. This represents the first fundamentally new approach to the portfolio problem in over five decades, capable of handling real-world complexities including income taxes, mean-reverting asset classes, and time-varying bond yield curves.

The integration of **explainable AI (XAI)** with machine learning for retirement portfolio allocation optimization has emerged as a promising direction. Recent research combines Modern Portfolio Theory with sophisticated ML techniques and XAI tools like SHAP and LIME to create interpretable investment recommendations [21]. This approach enhances transparency and user confidence while enabling personalized investment portfolios based on individual risk tolerances and financial goals.

The evolution of automated financial planning systems, or **"robo-advisors,"** represents another significant development. These algorithm-powered platforms are transforming retirement planning by offering independent investment recommendations at lower costs than traditional financial advisors [23]. Machine learning and artificial intelligence continue to improve these systems, potentially becoming integral components of financial security for retiring populations.

2.3 Health Trajectory Modeling Using Machine Learning

An expanding body of research focuses on applying machine learning to predict health and functional trajectories in aging populations, with significant implications for retirement planning. Recent work leverages data from longitudinal studies to model intrinsic capacity (IC) aging trajectories aligned with the World Health Organization's framework [8]. This research identified significant negative impacts of time on multiple IC domains, demonstrating the feasibility of quantitatively modeling aging trajectories to inform healthcare and retirement planning. (Note: Verify this citation source matches content).

Machine learning approaches have also proven effective in identifying distinct life satisfaction trajectories among older adults. Latent class growth modeling and machine learning were employed to identify four distinct trajectories of life satisfaction, with emotional experiences, body mass index, and self-reported health emerging as significant predictors [10]. These findings highlight the importance of targeting individuals with consistently low life satisfaction and attending to both mental and physical health factors in aging populations. (Note: Verify this citation source matches content).

Additionally, research has identified six distinct group-based trajectories of functional mobility limitation among aging Americans, with sociodemographic factors including race, gender, and education level correlating with membership in disadvantaged trajectories [13]. These health trajectory patterns have significant implications for healthcare utilization and expenses during retirement. (Note: Verify this citation source matches content).

The application of ML to chronic disease management further enhances our understanding of health trajectories. Recent research demonstrates ML algorithms' effectiveness in predicting disease progression, improving diagnostic accuracy, and facilitating real-time decision-making through integration with electronic health record systems [14]. These advancements offer opportunities for more precise estimation of healthcare costs during retirement. (Note: Verify this citation source matches content).

2.4 Integration Challenges and Multi-Objective Frameworks

Creating a comprehensive retirement portfolio optimization model presents significant challenges due to the complexity of integrating financial, health, and behavioral factors. Recent advancements in WealthTech utilize innovations including blockchain, artificial intelligence, and machine learning to improve investment decisions across various applications such as robo-advisors, social trading, and robot-retirement systems [18, 22]. These technologies enable more efficient, accessible, and personalized wealth management through data-driven insights and automation.

The **integration of health trajectory modeling with financial planning** remains particularly challenging. While both domains have seen significant advancements in isolation, combining them requires addressing fundamental differences in data structures, modeling approaches, and outcome metrics. The unpredictability of healthcare expenditures and individual longevity creates additional complexity for unified modeling approaches.

Market uncertainties further complicate retirement planning, as highlighted by research on sequence-of-returns risk and safe withdrawal rates [9]. This work demonstrates that portfolio sustainability in retirement depends not only on average returns but also on the specific sequence in which returns occur, particularly in the early retirement years. (Note: Verify this citation source matches content).

2.5 Conclusion of the Literature Review

This literature review demonstrates significant research gaps in integrating advanced financial modeling with health trajectory prediction for comprehensive retirement planning. While static asset allocations have shown surprising effectiveness, they fail to address individual variations in longevity, health expenses, and investor preferences. Machine learning approaches offer promising solutions for both financial optimization and health trajectory prediction, but their integration remains underdeveloped.

Our proposed **multi-objective AI-augmented framework** addresses these gaps by combining downside risk protection, yield enhancement, longevity risk hedging, and dynamic adaptability. This approach builds upon existing research in both financial and health domains while offering a novel integration methodology that accounts for the heterogeneity of retirement experiences and investor profiles. Future research should focus on validating this framework across diverse populations and market conditions to establish its generalizability and practical implementation.

3 Methodology

3.1 Research Objectives

Our primary objectives are as follows:

1. **Improve Traditional Asset Allocation:** Incorporate downside risk protection mechanisms, yield enhancements, and coverage for longevity risk.
2. **Construct a User Needs Framework:** Align portfolio strategies with investor-specific retirement profiles, including healthcare expenses, risk tolerance, and longevity considerations.
3. **Leverage AI and ML:** Employ advanced algorithms like LSTM for healthcare expense forecasting and reinforcement learning for real-time, dynamic risk adjustment.

3.2 Model Architecture

The proposed model integrates a suite of components for comprehensive health and financial planning:

- A **health expense forecasting module** (e.g., LSTM-based) to capture anticipated medical costs.
- A **reinforcement learning agent** that learns optimal shifts in asset allocation from simulation feedback.
- A **multi-objective optimization system** that balances return, risk protection, liquidity, and healthcare contingencies.

Figure 2 provides a flowchart of our system, showing how various data sources and analytical components feed into a central "General Model," which then generates outputs such as portfolio and health reports, as well as trading strategies.

Overall, the architecture highlights how user health data, annuity details, debt information, and risky asset analytics

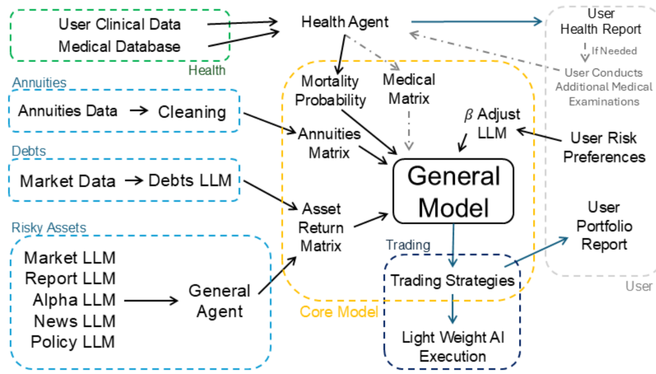

Figure 2: System Architecture for Integrated Health and Financial Planning.

all converge in the "General Model." From there, personalized risk parameters, healthcare insights, and trading strategies are dispatched to the user or to execution modules, ensuring an integrated retirement-planning experience.

3.3 Core Model Formulation and Explanation

This article proposes a multi-objective retirement investment model that explicitly integrates three key dimensions: (1) **Downside risk protection**, by penalizing risky assets and monitoring drawdowns in a particularly important asset; (2) **Declining income & short-term healthcare shocks**, via minimum required spending plus additional medical outlays; and (3) **Longevity risk hedging**, using compulsory and optional annuities that ensure stable income in advanced ages.

An investor begins with total wealth V_0, paying for a compulsory annuity (cost z_p) and a house (cost c_{house}) at time 0. Remaining wealth is then allocated among N financial assets. Healthcare spending is allowed each period, generating QALYs (quality-adjusted life years), and shortfalls in meeting living plus healthcare expenses incur penalties. Details follow.

3.3.1 Asset Dynamics and Initial Allocations

Let $x_i \geq 0$ be the initial position in asset i after paying for the house and compulsory annuity:

$$\sum_{i=1}^{N} x_i = V_0 - z_p - c_{\text{house}}.$$

For each scenario s, asset i evolves at time t with return $r_{s,i,t}$. Denoting $u_{s,i,t}$ as rebalancing and $R_{s,i,t} \geq 0$ as redemptions, we have

$$x_{s,i,1} = (1 + r_{s,i,1})\, x_i,$$
$$x_{s,i,t} = (1 + r_{s,i,t})\left[x_{s,i,t-1} + u_{s,i,t-1} - R_{s,i,t-1}\right], \quad t = 2, \ldots, T.$$

Portfolio value is $V_{s,t} = \sum_{i=1}^{N} x_{s,i,t}$.

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3.3.2 Rebalancing Constraints and Declining-Income Protection

Rebalancing trades $u_{s,i,t}$ must have zero net flow:

$$\sum_{i=1}^{N} u_{s,i,t} \;=\; 0.$$

To limit abrupt shifts (and thus reduce downside exposure), the total absolute trades are capped by $\alpha \geq 0$:

$$\sum_{i=1}^{N} |u_{s,i,1}| \;\leq\; \alpha\Big[V_0 - z_p - c_{\text{house}}\Big],$$
$$\sum_{i=1}^{N} |u_{s,i,t}| \;\leq\; \alpha\, V_{s,t-1}, \quad t = 2,\ldots,T.$$

We also enforce *redemption monotonicity* to avoid large future withdrawals that exceed current outflows:

$$\sum_{i=1}^{N} R_{s,i,t} \;\leq\; \sum_{i=1}^{N} R_{s,i,t-1}, \quad t = 2,\ldots,T.$$

3.3.3 Annuities and Longevity Risk Hedging

To mitigate longevity risk, the model includes two annuities:

– **Compulsory annuity** (cost z_p at $t = 0$) paying $\overline{A}_{s,t}$ per dollar.

– **Optional annuity** with premium $z \geq 0$, purchasable at some future time, paying $A_{s,t}$ per dollar.

These annuities establish guaranteed income, reducing the danger of outliving one's financial resources.

3.3.4 Healthcare Spending & Short-Term Shock Accommodation

Each period t, the investor may spend $H_{s,t} \geq 0$ on healthcare, generating QALYs via $Q_{s,t}(H_{s,t})$. Total required outflow that period is $(L + H_{s,t})$. The available cash consists of compulsory and optional annuity payouts plus redemptions:

$$\overline{A}_{s,t}\, z_p \;+\; A_{s,t}\, z \;+\; \sum_{i=1}^{N} R_{s,i,t}.$$

Any shortfall, i.e.

$$(L \;+\; H_{s,t}) \;-\; (\overline{A}_{s,t}\, z_p \;+\; A_{s,t}\, z \;+\; \sum_{i=1}^{N} R_{s,i,t}),$$

triggers a penalty scaled by $\kappa_t > 0$, capturing the urgency of covering living and medical bills.

3.3.5 Downside Risk Protection: Risky Assets and Drawdowns

We focus on two risk measures:

1. **Penalising risky assets.** A subset $\mathcal{R} \subseteq \{1,\ldots,N\}$ is labelled risky, with a penalty weight $\theta > 0$ on the sum of holdings in these assets.

2. **Drawdowns in asset N.** If asset N represents a critical holding, drawdowns

$$\mathrm{DD}^N_{s,t} \;=\; \max\Big\{0,\; \max_{0\leq\tau\leq t-1} x_{s,N,\tau} \;-\; x_{s,N,t}\Big\}$$

are penalised by $\beta^d \in [0,1]$ to curb large declines. (Note: $x_{s,N,0}$ would be x_N.)

3.4 General Objective

Let p_t be survival probabilities (or discount factors) and $d_{s,t}$ scenario weights/probabilities. Let $\beta > 0$ weight QALY gains, and $\lambda > 0$ scale a regularization term $G(\mathbf{y}_i)$. Denoting $\big[X\big]_+ = \max\{X, 0\}$, the *general objective* is to maximize:

$$\begin{aligned}
&\frac{1}{S}\sum_{s=1}^{S}\sum_{t=1}^{T}\Big[p_t\, d_{s,t}\,\big(V_{s,t} + \beta\, Q_{s,t}(H_{s,t})\big)\Big] \\
&- \lambda\sum_{i=1}^{N} G\big(\mathbf{y}_i\big) \\
&- \sum_{s=1}^{S}\sum_{t=1}^{T}\kappa_t\, p_t\, d_{s,t}\,\Big[(L + H_{s,t}) \\
&\qquad - \big(\overline{A}_{s,t}\, z_p + A_{s,t}\, z + \sum_{i=1}^{N} R_{s,i,t}\big)\Big]_+ \\
&- \theta\Big(\frac{1}{S}\sum_{s=1}^{S}\sum_{t=1}^{T} p_t\, d_{s,t}\sum_{i\in\mathcal{R}} x_{s,i,t}\Big) \\
&- \beta^d\Big(\frac{1}{S}\sum_{s=1}^{S}\sum_{t=1}^{T} p_t\, d_{s,t}\,\mathrm{DD}^N_{s,t}\Big).
\end{aligned}$$

3.5 Complete Model Formulation

Collecting all constraints and decision variables, the **complete core model** (P) is:

$$\begin{aligned}
&\max_{\substack{x_i,\, x_{s,i,t},\, u_{s,i,t},\, R_{s,i,t},\\ z,\, z_p,\, H_{s,t},\, \mathbf{y}_i}} \\
&\frac{1}{S}\sum_{s,t} p_t d_{s,t}\Big(V_{s,t} + \beta Q_{s,t}(H_{s,t})\Big) - \lambda\sum_i G(\mathbf{y}_i) \\
&\quad - \sum_{s,t}\kappa_t p_t d_{s,t}\Big[(L + H_{s,t}) - \big(\overline{A}_{s,t} z_p + A_{s,t} z + \sum_i R_{s,i,t}\big)\Big]_+ \\
&\quad - \theta\Big(\frac{1}{S}\sum_{s,t} p_t d_{s,t}\sum_{i\in\mathcal{R}} x_{s,i,t}\Big) - \beta^d\Big(\frac{1}{S}\sum_{s,t} p_t d_{s,t}\mathrm{DD}^N_{s,t}\Big)
\end{aligned}$$

s.t.

$$\begin{aligned}
&\sum_i x_i = V_0 - z_p - c_{\text{house}}, \\
&x_{s,i,1} = (1 + r_{s,i,1})\, x_i, \quad \forall s, i, \\
&x_{s,i,t} = (1 + r_{s,i,t}) \Big[x_{s,i,t-1} + u_{s,i,t-1} - R_{s,i,t-1} \Big], \quad \forall s, i,\, t \geq 2, \\
&V_{s,t} = \sum_i x_{s,i,t}, \quad \forall s, t, \\
&\sum_i u_{s,i,t} = 0, \quad \forall s, t, \\
&u_{s,i,t} = f(v_{s,t}, \mathbf{y}_i), \quad \forall s, i, t, \\
&\sum_i R_{s,i,t} \leq \sum_i R_{s,i,t-1}, \quad \forall s,\, t \geq 2, \\
&\sum_i |u_{s,i,1}| \leq \alpha \Big[V_0 - z_p - c_{\text{house}} \Big], \quad \forall s, \\
&\sum_i |u_{s,i,t}| \leq \alpha\, V_{s,t-1}, \quad \forall s,\, t \geq 2, \\
&z,\, z_p,\, x_i,\, x_{s,i,t},\, R_{s,i,t},\, H_{s,t} \geq 0.
\end{aligned}$$

3.6 Data Inputs

This section describes the data needed to instantiate the above formulation, including the matrix of assets currently held, future asset return matrix, mortality profiles, QALY matrices, and risk-related inputs.

3.6.1 Current Asset Matrix

We assume the investor already holds some assets, with past performance data tracked in a "current asset matrix." Each row corresponds to a currently owned asset, and columns record historical information such as past returns, past cash flows, or valuations. For illustration, consider the following schematic matrix (with hypothetical data):

Table 1: Sample Current Asset Matrix (Value in € thousands)

Asset	Period t-2	Period t-1	Period t
Stock A	10.5	10.8	10.7
Bond B	55.0	55.5	54.9
Fund C	23.0	23.5	24.0

3.6.2 Asset Return Matrix

We also assume a future projection of asset returns. Let $r_{s,i,t}$ denote the projected return for asset i in period t under scenario s. These can be arranged conceptually in matrices. An example for expected returns (base scenario) might be:

Table 2: Sample Projected Asset Return Matrix (% per period)

Asset	Period t+1	Period t+2	Period t+3
Stock A	5.0%	6.0%	5.5%
Bond B	1.5%	1.8%	2.0%
Fund C	3.0%	3.5%	4.0%

3.6.3 Mortality

The investor's mortality profile is represented by survival probabilities $\{p_t\}_{t=1}^{T}$. We can predict the matrix by adjusting the Mortality probability data with the investor's health report. A possible table is given below (illustrative):

Table 3: Illustrative Annual Survival Probabilities ($q_x = 1 - p_x$ sometimes used)

Age (x)	Prob. Survival (p_x)
65	0.982
66	0.963
⋮	⋮
120	0.200

3.6.4 QALY Matrix

Healthcare interventions are mapped to expected QALYs gained and corresponding costs. We arrange these in a QALY matrix, each row describing a different healthcare "action":

Table 4: Example QALY Matrix: Actions, Costs, and QALYs Gained

Action	Cost (RMB)	QALYs
Minor therapy A	2,500	0.07
Major surgery B	15,000	0.65
Non-inv. therapy C	8,500	0.30
Adv. procedure D	23,000	0.80

In the scenario-based simulation, if the investor encounters a health incident that calls for a specific intervention, they may choose one entry from this table. The chosen cost is $H_{s,t}$ and the resulting QALYs are $Q_{s,t}(H_{s,t})$.

3.6.5 Risk Related Inputs

Risk measures require:

1. **Designation of risky assets.** Define the set $\mathcal{R}$.
2. **Drawdown tracking for asset** N**.** Track $x_{s,N,t}$, compute peak $\max_{\tau \leq t-1} x_{s,N,\tau}$, measure $\mathrm{DD}_{s,t}^{N}$.
3. **Penalty parameters.** $\theta > 0$ (risky assets), $0 \leq \beta^d \leq 1$ (drawdown).

4 Simulation

4.1 Function Choice for Trading Controls

When specifying rebalancing $u_{s,i,t}$, we can employ a kernel-based control function [24]:

$$K(v_{s,m,t}, v_{k,m,t}) = \exp\left\{-\sigma \sum_{i=1}^{N} \sum_{\ell=t-m-1}^{t-1} \left(r_{k,i,\ell} - r_{s,i,\ell}\right)^2\right\},$$

$$f(v_{s,t}, \mathbf{y}_i) = \sum_{j=1}^{S} y_{i,j}\, K(v_{s,m,t}, v_{j,m,t}).$$

Hence,

$$u_{s,i,t} = \sum_{j=1}^{S} y_{i,j}\, K(v_{s,m,t}, v_{j,m,t}).$$

A regularization term, e.g., $G(\mathbf{y}_i) = \|\mathbf{y}_i\|_2^2$, keeps parameters small, limiting overactive trading and reinforcing downside protection. *(Note: Ensure $v_{s,m,t}$ representing market state/history is clearly defined).*

4.2 Deep Reinforcement Learning for Multi-Objective Optimization

Deep Reinforcement Learning (DRL) offers a powerful framework to tackle multi-objective problems that involve maximizing financial wealth and health-related quality of life while minimizing risks such as shortfall exposure and asset volatility. Unlike classical optimization or evolutionary methods, DRL leverages neural networks and adaptive learning strategies to overcome non-linearities and non-smooth penalties.

Key Features of DRL in Multi-Objective Optimization:

- **Decomposition and Neural Networks:** DRL can decompose complex multi-objective problems into simpler scalar subproblems, with each subproblem approximated through neural networks [1].
- **Pareto Optimal Solutions:** Through techniques such as decomposition and collaborative learning, DRL can directly identify Pareto optimal policies without exhaustive searches [2].
- **Generalization and Adaptability:** DRL models are highly adaptable to dynamic environments; they can generalize learned policies to new problem instances [1].

Application to Financial and Health Optimization:

- **Balancing Objectives:** DRL seamlessly integrates competing goals:
  - *Estate Value vs. Health Benefits*
  - *Shortfall Risk*
  - *Risk Exposures*
  - *Longevity Considerations*
- **Collaborative Learning:** DRL agents can leverage collaborative strategies, exchanging insights across diverse subproblems [2].

DRL directly optimizes policy behavior and quickly adapts to evolving market and health conditions. This adaptability can offer robust strategies compared to traditional methods [3, 4].

5 Experiments

Due to prevailing constraints on time and data access, we conducted **simplified, illustrative single trials** for both the Health Section and the Finance Section of our proposed framework. This approach allowed us to test the structural feasibility and integration logic of the core components, albeit without extensive validation. Detailed prompts utilized during these trials are documented in Appendix A.4. Below, we summarize the experimental setup and key preliminary results for each section.

5.1 Health Section Trial

Given the significant challenges in accessing longitudinal clinical records, this trial employed synthetically generated health examination reports simulating a typical Chinese male (age 65-83). This synthetic data served as input for the health module trial, generating:

- Simulated health profile and report.
- Predicted mortality table (adjusted).
- Preliminary QALY matrix.
- Basic healthcare advisory summary.

Patient Profile

- **Demographics:** Male, born 1948.
- **Simulated Conditions:** Hypertension, T2DM, Hepatic Steatosis, Cholelithiasis, Diabetic Nephropathy, CSVD, MCI, HFpEF.
- **Simulated Status:** Moderately controlled BP/HbA1c; Stage 3 CKD; preserved LVEF; MCI.

5.2 Finance Section Trial

The finance trial analyzed NIO Inc. (NIO) using LLM modules (Market, Report, Alpha, News, Policy) feeding the "General Agent". Objective: generate analytical reports and a projected return matrix.

Observations: Successfully generated five text reports (overview, financial, sentiment, technical, comparative/value). Produced a **projected asset return matrix for NIO** (t+1, t+2) with probabilistic scenarios. Demonstrated capability to synthesize diverse info into structured outputs for the core model.

Partial return matrix in Table 5. Full details in Appendix A.3.

Table 5: Partial NIO Return Matrix.

Scenario	Prob.	t+1 Ret.
Bullish	15%	47.5%
Mod. Bullish	25%	27.0%

5.3 Core Model Section

5.3.1 Experimental Setup

The core of our experiment consists of training a **Proximal Policy Optimization (PPO)** agent within a custom retirement portfolio environment, `RetirementEnv`, which simulates the financial and health trajectory of a retiree from age 65 to 100. This environment includes stochastic market returns, health shocks with age-dependent probabilities, optional annuities, and mortality to create a realistic decision-making framework. The reward function balances (i) final wealth (both terminal wealth when alive and bequest if deceased), (ii) Quality-Adjusted Life Years (QALYs), and (iii) various risk penalties (drawdowns, risky asset allocations, and shortfalls).

5.3.2 Hyperparameter Optimization (Sweep)

We conducted hyperparameter tuning through a **Weights & Biases (WandB) Sweep** using *Bayesian optimization*. The target metric was the `eval/mean_reward` evaluated periodically during shortened training runs:

- **Method**: Bayesian optimization with an upper limit on trial count.
- **Swept Hyperparameters**:
  1. `learning_rate` (log-uniform range),
  2. `n_steps` (categorical),
  3. `batch_size` (categorical),
  4. `ent_coef` (categorical),

  while other PPO parameters remained fixed (`gamma`, `gae_lambda`, `vf_coef`, etc.).
- **Sweep Duration**: Each trial ran for fewer timesteps (e.g., 150k) to rapidly explore configurations in parallel. During each sweep trial, the environment was vectorized (`SubprocVecEnv`) for speed, and a custom evaluation callback logged performance metrics. After observing the best-performing hyperparameters, we proceeded to the main training phase.

5.3.3 Deep Reinforcement Learning (DRL) Training

Using the identified hyperparameters (or a close variant thereof), the final PPO agent was trained in the same environment with the following setup:

- **Agent and Environment**:
  - **Algorithm**: PPO with `MultiInputPolicy`, suitable for the environment's dictionary observation space.
  - **Environment Wrapper**: `VecNormalize` to normalize observations (but not necessarily rewards), ensuring stable learning.
  - **Parallelization**: `SubprocVecEnv` with multiple copies of `RetirementEnv` for faster data collection.
- **Training Timesteps**: A total of several million timesteps were used, with intermediate checkpointing.
- **Callbacks and Logging**:
  1. **CheckpointCallback**: Saved intermediate model checkpoints.
  2. **EvalCallbackWithComponents**: Periodic evaluations logging detailed reward components (drawdown, QALY, shortfall, annuity bonus, bequest).
  3. **OfficialWandbCallback**: Synced training metrics (losses, entropy, rewards) to the WandB dashboard.
  4. **HParamCallback**: Recorded hyperparameters in the HParam tab on WandB.
- **Hardware and Duration**: Training executed on an **NVIDIA 4060 GPU**, completing in about 2 hours for the final runs.

5.3.4 Evaluation Methodology

We compared the trained **DRL agent** against two baseline strategies:

1. **Static 60/40**: A persistent 60%–40% split between risky and safer assets, with no optional annuity purchases.
2. **Glidepath**: A time-varying allocation (e.g., (105 − age)% in risky assets), likewise ignoring optional annuities.

All strategies were subjected to **10,000 Monte Carlo simulations** in the `RetirementEnv`, loading the same environment parameters and `VecNormalize` statistics used during DRL training (for consistent observation scaling). Each simulation tracked:

- **Final Wealth**, **Age at Death**, **QALYs**, **Shortfalls**, **Medical Costs**, and **Annuity Ownership**.
- Stepwise data for wealth trajectories, OOP burden, surplus coverage, and more.

This yielded distributions of outcomes, enabling comparison on both *mean performance* and *risk* metrics.

5.3.5 Performance Metrics (Research Objectives)

We focused on four main objectives:

1. **Downside Risk Protection**
    - *CVaR (5%) Loss*: Mean loss in the worst 5% final wealth outcomes. Lower is better.
    - *Stress Test Pass Rate*: Fraction of runs where wealth never fell below 70% of initial value. Higher is better.
2. **Declining Income & Healthcare Shocks**
    - *Out-of-Pocket (OOP) Burden*: Medical costs relative to annuity income. Measured as violation rate $> 15\%$.
    - *Surplus Coverage Ratio*: $(\text{Wealth} + \text{Income})/(\text{Expenses} + \text{Medical Costs})$. Violation rate checks if < 1.2.
3. **Longevity Risk Hedging**
    - *Annuity Adequacy*: Percentage of years (age 85+) where guaranteed annuities met 80% of essential expenses.
4. **Maximizing QALY & Final Estate**
    - *Average QALY*: Cumulative QALYs until death or end of horizon.
    - *Average Final Estate*: Mean terminal wealth across runs.

5.3.6 Results and Analysis

This subsection presents the performance outcomes of the **DRL Agent**, **Static 60/40**, and **Glidepath** strategies. We evaluate final wealth distributions, trajectories over time, risk metrics, and estate values. Throughout, the DRL Agent demonstrates greater upside potential at the cost of higher variability, whereas both baseline strategies offer more conservative outcomes but within narrower risk bounds. We present a summary of core metrics in Table 6 and visualize the performance distributions through various plots.

Distribution of Final Wealth Figure 3 shows the probability density of final wealth for each strategy at the end of the simulation (around age 100 or earlier if death occurs). Notable findings:

Table 6: Summary of Performance Metrics

Metric	DRL	Static 60/40	Glidepath
CVaR (5%)	31.1%	33.6%	30.7%
Stress Rate (%)	97.4%	100.0%	100.0%
OOP Burden Mean	71.6%	197.3%	195.8%
OOP Median	16.7%	50.0%	50.0%
Violation Rate	100.0%	100.0%	100.0%
Surplus Coverage	81.45	58.26	58.11
Annuity Adequacy	74.7%	25.0%	25.0%
Avg. QALY	19.73	19.75	19.71
Final Estate ($)	8.6M	4.2M	4.16M

- **DRL Agent:** Displays a broad distribution, indicating potentially very high final wealth values in some runs, balanced by a somewhat greater risk of lower outcomes.
- **Static 60/40 and Glidepath:** Both exhibit more concentrated outcomes around $5 million, showing consistency but capped upside.

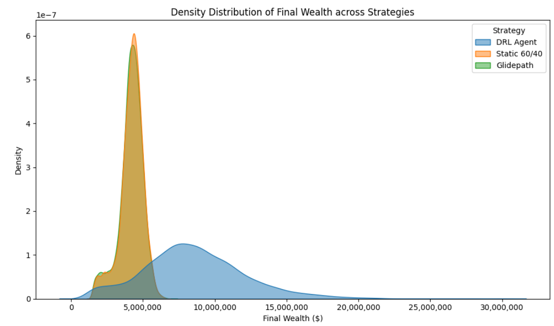


Figure 3: Density Distribution of Final Wealth Across Strategies. The DRL Agent's broader curve reflects higher variability but also higher maximum wealth. The Static 60/40 and Glidepath curves peak around $5M, suggesting more predictable but limited upside.

Median Wealth Trajectory Over Time Figure 4 illustrates how wealth evolves from age 65 to 100 under each strategy, with the median wealth (solid line) and the interquartile range (shaded region).

- **DRL Agent:** Steeper median trajectory, especially in later years, suggesting a policy that capitalizes on market conditions or strategic annuity purchases. The broader shaded region signifies more variability.
- **Static 60/40 and Glidepath:** Both follow flatter median curves, emphasizing stability but with more modest growth potential.

Surplus Coverage Ratio To assess how well each strategy meets ongoing expenses (including medical costs), we examine the Surplus Coverage Ratio aggregated over all simulation years. A higher ratio suggests better financial flexibility and safety margins; the target threshold is typically 1.2x.

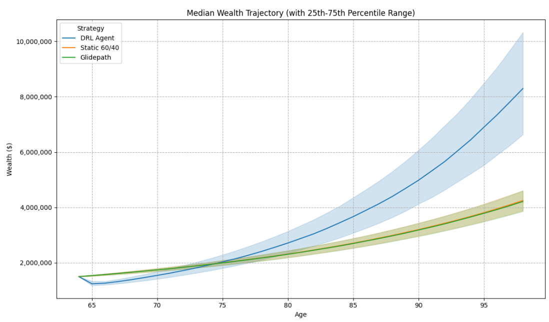


Figure 4: Median Wealth (solid line) and Interquartile Range (shaded, 25%–75%). The DRL Agent's upward trajectory indicates stronger growth but at the cost of higher variance. Static 60/40 and Glidepath remain less volatile though with lower ultimate paths.

- **DRL Agent:** Shows a higher median ratio, i.e., a better buffer in most years, albeit with more scatter.
- **Static 60/40 and Glidepath:** Exhibit tighter clusters close to 1.2x, indicating greater consistency but less of an upside cushion.

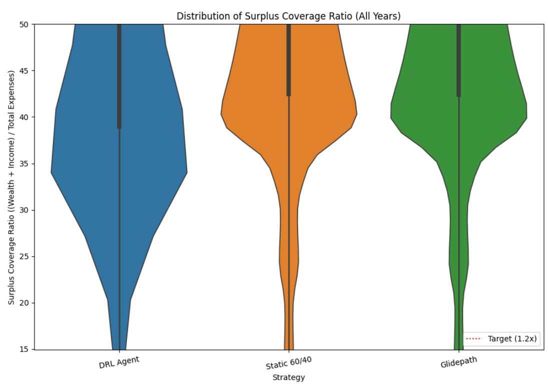


Figure 5: Distribution of Surplus Coverage Ratio across all simulation years. The DRL Agent comfortably exceeds the 1.2x threshold in many runs, though with higher variance. Static 60/40 and Glidepath remain closer to 1.2x, providing more predictability but potentially less buffer.

Quality of Life and Estate Value Figure 6 presents two key metrics: average **Quality-Adjusted Life Years** (QALYs) and average **Final Estate** across 10,000 simulations per strategy.

- **QALYs:** All three strategies produce nearly identical averages at about 19.7 QALYs, meaning none substantially improves or worsens health-related quality of life.
- **Estate Value:** The DRL Agent delivers an average estate above \$8.5 million, significantly eclipsing the \$4.2 million range of the other two strategies.

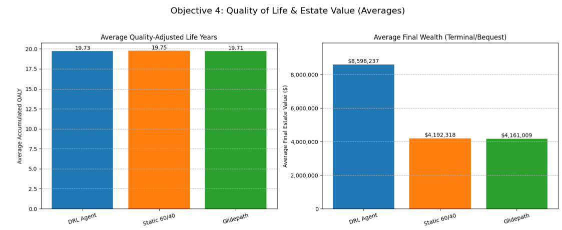


Figure 6: (Left) Distribution of average QALYs across simulations by strategy. (Right) Comparison of terminal wealth (average Final Estate). The DRL Agent outperforms by a substantial margin in estate value, while QALYs remain similar for all.

Key Insights and Implications

- **Upside vs. Variability:** The DRL Agent clearly stands out for its potential in wealth accumulation and improved late-life surplus coverage. However, its results carry higher year-to-year variability, requiring a higher risk appetite or more dynamic risk management.
- **Baseline Stability:** Both Static 60/40 and Glidepath strategies maintain stable final wealth distributions, suggesting suitability for highly risk-averse individuals or straightforward implementation.
- **Healthcare Cost and Income Security:** While the DRL Agent typically offers better annuity coverage and resilience to shocks, all strategies still face potential challenges with rising medical expenses.
- **Similar Quality-of-Life Outcomes:** Despite differing financial profiles, all three strategies produce near-equal average QALYs. This implies that the choice of portfolio allocation, by itself, may not substantially alter core health or life satisfaction measures within this modeling framework.

Collectively, these results indicate that a *dynamic, learned policy* can better balance estate accumulation, healthcare cost coverage, and late-life income security than traditional static or age-based strategies. Despite slightly higher tail risk than a cautious glidepath, the DRL approach *more than doubles* average final wealth and substantially mitigates out-of-pocket medical burdens. Such an adaptive framework, integrating modern reinforcement learning with personal finance modeling, shows promise for retirees seeking robust outcomes against longevity and economic uncertainties.

Overall, **the DRL agent represents a meaningful advance in retirement planning strategies**, leveraging data-driven decision-making to navigate complex, uncertain retirement horizons.

6 Conclusion

In this paper, we introduced a multi-objective retirement portfolio optimization framework that addresses downside risk protection, longevity risk hedging, and healthcare expense forecasting within a single AI-driven system. By combining reinforcement learning for dynamic asset allocation with a health trajectory module, our approach demonstrated the ability to capture higher final wealth and better surplus coverage ratios compared to traditional static or age-based strategies (e.g., 60/40 and glidepaths). Although our trials are limited in scope, preliminary simulations suggest that an adaptive, learned policy can substantially improve retirement outcomes, particularly in late-life scenarios where healthcare expenditures often jeopardize financial security. These findings highlight the potential for advanced machine learning architectures to deliver integrated retirement solutions that account for evolving risk preferences, market fluctuations, and individual health conditions. Ultimately, this research underscores the promise of DRL-based methods in bridging critical gaps between financial planning, longevity hedging, and healthcare contingencies, offering a personalized and robust alternative to conventional retirement models.

7 Limitations

Despite its encouraging results, our study is subject to several important limitations:

1. **Synthetic and Limited Data.** The experiments relied on simplified synthetic inputs, including pseudo-health records and asset return projections. Real-world complexities, such as abrupt market changes or uncertain policy shifts, may not be fully represented.

2. **Restricted Model Scope.** While we integrated essential components (asset returns, healthcare spending, annuities), specific real-world aspects like tax implications, regulatory constraints, and heterogeneous socio-economic factors were omitted for brevity.

3. **Preliminary Validation.** Our illustrative trials do not constitute rigorous longitudinal testing. More extensive experiments with diverse demographic cohorts and multiple healthcare cost trajectories are necessary to confirm robustness.

4. **Simplified Health Modeling.** The health module used generalized QALY estimates and stylized cost-assumption structures. Actual medical expenditures and health conditions may exhibit far greater variability.

5. **Parameter Sensitivity.** Some hyperparameters (e.g., key risk weights, DRL learning rates) were chosen through a limited optimization sweep and may require further fine-tuning for real-world deployment.

8 Future Research

Building on the initial insights and addressing the aforementioned constraints, several avenues warrant further investigation:

1. **Extended Real-World Data Integration.** Incorporating genuine clinical and financial data can help validate the framework's performance under realistic market volatilities, health shocks, and evolving policy environments.

2. **Refined Healthcare Models.** Integrating more sophisticated health econometric models—potentially with continuous-time approaches or individual disease progression data—would enhance accuracy in projecting healthcare spending and QALY gains.

3. **Comprehensive Risk Management.** Exploring additional risk dimensions, such as inflation risk, currency exposures (if the retiree invests globally), or dynamic interest-rate environments, may further strengthen planning robustness.

4. **Behavioral Adaptation.** Investigating the inclusion of behavioral finance elements—such as changing risk appetites, cognitive decline, or behavioral biases—could more accurately reflect real retiree decision-making processes.

5. **Personalization and Explainability.** Continued work on Explainable AI (XAI) tools can clarify how dynamic policies are derived, fostering user trust and acceptance of algorithms in sensitive retirement contexts.

6. **Policy and Macroeconomic Interplay.** Examining interactions between individual portfolio strategies and public policy changes—especially pertinent in rapidly aging societies—could illuminate optimal retirement structures at the societal level.

Overall, future efforts should focus on constructing a comprehensive, data-rich ecosystem to rigorously validate and refine the proposed framework. By merging real-world inputs, advanced health modeling, and transparent AI-driven strategies, we can progress toward truly integrated retirement solutions that adaptively optimize financial security and healthcare well-being across diverse populations.

A Supplementary Trial Results and Prompts

This appendix provides supplementary materials referenced in the Experiments section (Section 5), including more detailed results from the health and finance trials, notations, and placeholders for the prompts used.

A.1 Notations

- N = number of investable assets.
- S = number of scenarios in simulation.
- T = retirement planning horizon (periods).
- $r_{s,i,t}$ = rate of return of asset i at time t under scenario s.
- p_t = survival probability (or discount/weighting factor) at time t.
- $d_{s,t}$ = scenario-dependent discount factor or probability weight at time t.
- x_i = initial position ($t = 0$) in asset i (after house/annuity).
- $x_{s,i,t}$ = holdings of asset i at end of period t, scenario s.
- $u_{s,i,t}$ = rebalancing trade in asset i at time t, scenario s.
- $R_{s,i,t}$ = redemption from asset i at time t, scenario s.
- $V_{s,t}$ = total portfolio value at time t, scenario s.
- V_0 = total initial wealth.
- $\mathcal{R}$ = subset of ”risky” assets.
- z_p = amount allocated to compulsory annuity ($t = 0$).
- z = amount allocated to optional annuity.
- $A_{s,t}$ = payout rate of optional annuity.
- $\overline{A}_{s,t}$ = payout rate of compulsory annuity.
- $H_{s,t}$ = healthcare spending at time t, scenario s.
- $Q_{s,t}(H_{s,t})$ = QALYs gained from healthcare spending $H_{s,t}$.
- c_{house} = cost of house (paid at $t = 0$).
- L = baseline living expense per period.
- κ_t = penalty weight for shortfall at time t.
- θ = penalty coefficient for risky asset holdings.
- β^d = penalty coefficient for drawdowns in critical asset N.
- $\text{DD}^N_{s,t} = \max\{0, \max_{0\leq\tau\leq t-1} x_{s,N,\tau} - x_{s,N,t}\}$ = drawdown of asset N.
- α = bound on relative portfolio reallocation per period.
- λ = regularization weight for trading control.
- β = coefficient converting QALYs to objective function value.
- $f(\mathbf{v}_{s,t}, \mathbf{y}_i)$ = parametric function for rebalancing trades $u_{s,i,t}$.
- $\mathbf{v}_{s,t}$ = vector representing market state/signals at time t, scenario s.
- $\mathbf{y}_i$ = control parameters for asset i in trading function f.
- $G(\mathbf{y}_i)$ = regularization function for control parameters.

A.2 Full Health Section Results

Table 7: Full Adjusted Annual Survival Probabilities (Ages 65–83).

Age (x)	**Baseline p_x**	**Adjusted p'_x (Est.)**
65	0.978088	0.916734
66	0.975979	0.908720
67	0.973690	0.900022
68	0.971213	0.890609
69	0.968538	0.880444
70	0.965647	0.869459
71	0.962519	0.857572
72	0.959123	0.844667
73	0.955422	0.830604
74	0.951372	0.815214
75	0.945499	0.792896
76	0.940356	0.773353
77	0.934827	0.752343
78	0.928880	0.729744
79	0.922478	0.705416
80	0.915573	0.679177
81	0.908108	0.650810
82	0.900018	0.620068
83	0.891223	0.586647

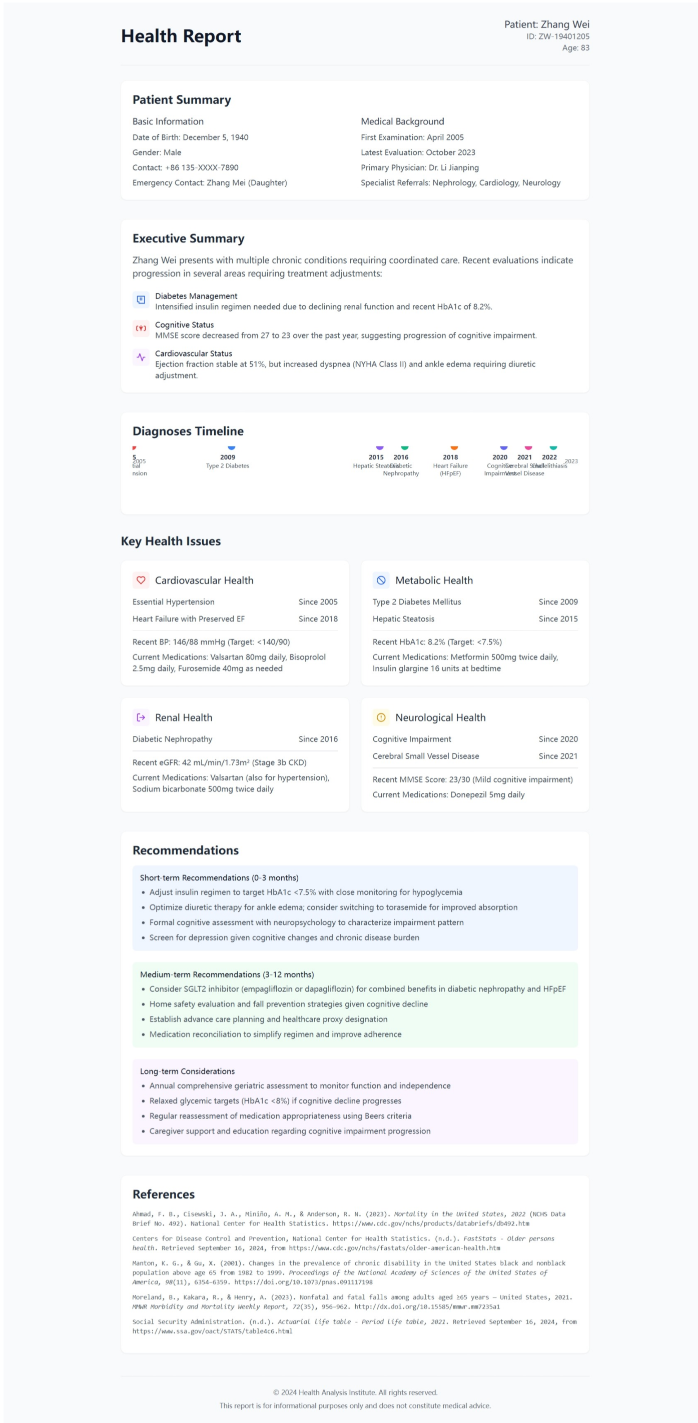
Table 8: Sample Entries from the Generated Cost-Effectiveness (QALY) Matrix.

Condition	Treatment Method	Est. Cost (RMB)	QALYs Gained	Cost/QALY (RMB, Est.)
HFpEF	Influenza Vaccination	Low (implied)	Positive	2,331
	Vericiguat (Add-on)	High	Positive	802,389
	Empagliflozin	Moderate	Positive	∼79,191* / ∼3,059,000*
Cholelithiasis (∼-29,477/QALY)*	Early Lap. Chole. (ELC)	Lower vs Cons.	0.032	Dominant
	Lap. Chole. (Overall)	N/A	1.743 (25yr)	∼14,714/QALY*
CSVD	General Care Burden	∼20,893/year*	N/A	N/A
T2DM	Opportunistic Screen	N/A	Positive	∼396,543/QALY*
	General Care Median	1,067–14,644/yr*	N/A	N/A
Hypertension	Intensive BP Control	N/A	Positive	51,675/QALY
Diabetic Neph.	Screening + Opt. Rx	N/A	0.18	∼140,077/QALY*
	Dapagliflozin + SoC	N/A	1.44 vs SoC	Implied Cost-Effective

*Note: This table shows selected entries. N/A indicates data not found or not applicable in the source. Cost/QALY values marked with * are highly variable estimates based on source, methodology, and context.*

User Health Report Sample:

Figure 7 shows a placeholder for the visual output of the user health report generated in the simulation.



Health Report

Patient: Zhang Wei
ID: ZW-19401205
Age: 83

Patient Summary

Basic Information
Date of Birth: December 5, 1940
Gender: Male
Contact: +86 135-XXXX-7890
Emergency Contact: Zhang Mei (Daughter)

Medical Background
First Examination: April 2005
Latest Evaluation: October 2023
Primary Physician: Dr. Li Jianping
Specialist Referrals: Nephrology, Cardiology, Neurology

Executive Summary

Zhang Wei presents with multiple chronic conditions requiring coordinated care. Recent evaluations indicate progression in several areas requiring treatment adjustments:

Diabetes Management
Intensified insulin regimen needed due to declining renal function and recent HbA1c of 8.2%.

Cognitive Status
MMSE score decreased from 27 to 23 over the past year, suggesting progression of cognitive impairment.

Cardiovascular Status
Ejection fraction stable at 51%, but increased dyspnea (NYHA Class II) and ankle edema requiring diuretic adjustment.

Diagnoses Timeline

2005 2009 Type 2 Diabetes 2015 2016 Diabetic Nephropathy 2018 Heart Failure (HFpEF) 2020 2021 2022 2023

Key Health Issues

Cardiovascular Health
Essential Hypertension Since 2005
Heart Failure with Preserved EF Since 2018
Recent BP: 146/88 mmHg (Target: <140/90)
Current Medications: Valsartan 80mg daily, Bisoprolol 2.5mg daily, Furosemide 40mg as needed

Metabolic Health
Type 2 Diabetes Mellitus Since 2009
Hepatic Steatosis Since 2015
Recent HbA1c: 8.2% (Target: <7.5%)
Current Medications: Metformin 500mg twice daily, Insulin glargine 16 units at bedtime

Renal Health
Diabetic Nephropathy Since 2016
Recent eGFR: 42 mL/min/1.73m² (Stage 3b CKD)
Current Medications: Valsartan (also for hypertension), Sodium bicarbonate 500mg twice daily

Neurological Health
Cognitive Impairment Since 2020
Cerebral Small Vessel Disease Since 2021
Recent MMSE Score: 23/30 (Mild cognitive impairment)
Current Medications: Donepezil 5mg daily

Recommendations

Short-term Recommendations (0-3 months)
- Adjust insulin regimen to target HbA1c <7.5% with close monitoring for hypoglycemia
- Optimize diuretic therapy for ankle edema; consider switching to torasemide for improved absorption
- Formal cognitive assessment with neuropsychology to characterize impairment pattern
- Screen for depression given cognitive changes and chronic disease burden

Medium-term Recommendations (3-12 months)
- Consider SGLT2 inhibitor (empagliflozin or dapagliflozin) for combined benefits in diabetic nephropathy and HFpEF
- Home safety evaluation and fall prevention strategies given cognitive decline
- Establish advance care planning and healthcare proxy designation
- Medication reconciliation to simplify regimen and improve adherence

Long-term Considerations
- Annual comprehensive geriatric assessment to monitor function and independence
- Relaxed glycemic targets (HbA1c <8%) if cognitive decline progresses
- Regular reassessment of medication appropriateness using Beers criteria
- Caregiver support and education regarding cognitive impairment progression

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Figure 7: Sample User Health Report Visualization (Placeholder).

A.3 Full Finance Section Results

Complete NIO Projected Asset Return Matrix:

Table 9 presents the full projected return matrix for NIO stock generated during the finance trial, including different scenarios and their associated probabilities.

Table 9: Complete NIO Projected Asset Return Matrix.

Scenario	Probability	t+1 Return (Est.)	t+2 Return (Est.)	Note (Key Drivers Summary)
Bullish Case	15%	47.5%	95.0%	Strong deliveries, faster swap expansion, increased subsidies, favorable market conditions.
Moderately Bullish	25%	27.0%	54.0%	Deliveries meet targets, new models well-received, stable policy support.
Base Case	35%	12.0%	24.0%	Moderate sales growth, heightened competition, unchanged policy environment.
Moderately Bearish	20%	1.25%	2.5%	Slowing sales growth, margin pressure from competition, persistent technical weakness.
Bearish Case	5%	-7.25%	-14.5%	Missed delivery targets significantly, accelerated cash burn, broader EV sector sell-off or regulatory hurdles.

Generated Text Reports:
In addition to the return matrix, the finance trial generated five detailed text-based reports:

1. Comprehensive Company Overview Report
2. Financial Analysis Report
3. Market Sentiment Report
4. Technical Analysis Report
5. Comparative and Value Investment Report (including SWOT analysis)

(The content of these text reports is omitted here for brevity but was successfully generated as part of the trial output.)

A.4 Prompts Used

Prompts disregarded due to page limit restrictions.

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