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Enhancing U.S. retirement security and financial resilience through AI-Driven predictive analytics

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Abstract
All over the world, there are constant questions around the best way to ensure that elderly citizens enjoy their later years with significant Retirement Funds, not marred by the downturns of the economy. The United States stands at a demographic and fiscal crossroads, characterized by an aging population, rising healthcare expenditures and increasing pressure on public and private retirement systems.
Within this challenging context, a pressing problem emerges: millions of Americans are projected to face significant financial insecurity in their retirement years, threatening both individual well-being and broader economic stability. Let's paint what the future potentially looks like: retirement systems are unable to support millions of Americans in their retirement, which means a fall in purchasing power, which in turn triggers an economic crisis. Of course the US Government could begin sending out Stimulus packages to these individuals but it wouldn't work for too long and would be too expensive.
This impending crisis exposes a significant issue in prevailing retirement planning frameworks, which predominantly rely on static, deterministic models. These models, often based on linear projections and historical assumption, fail to capture the dynamic, non-linear and highly uncertain nature of a retiree's financial journey, which is subject to market volatility, health shocks, longevity risk and evolving economic policies. Take the current US economic climate, with Tariffs and the subsequent surge in food prices, the economy is evidently harder than it may have been six months ago or two years ago.
The problem? The US retirement systems don't take any of these external factors into account in its planning, which in turn leaves the Retirees at the mercy of brutal economic downturns.
The problem can be traced to the nature of retirement planning models which are static, not predictive or dynamic. These systems do not evolve in response to external circumstances affecting the economy.
This study proposes a paradigm shift by leveraging the power of AI and predictive analysis to develop a dynamic, probabilistic model for individual retirement preparedness and financial resilience.
By integrating diverse datasets including: market performance, health statistics, macroeconomic indicators, and personal financial record, machine learning algorithms can generate personalized, forward-looking assessments of retirement outcomes under a diverse set of future states.

Keyword: AI-driven predictive analytics, retirement security, financial resilience, aging population, dynamic modeling, economic stability, healthcare costs

Introduction

The contribution of this research is threefold

For individuals, it offers a more nuanced and realistic tool for planning, empowering proactive adjustments.

- For policymakers, it provides a detailed, data-driven perspective with which to evaluate the effectiveness of existing social safety nets and design targeted interventions.
- For financial institutions, it unveils new strategies for developing innovative products that address the specific risks faced by retiring clients. Ultimately, this study moves beyond the limitations of static planning to offer a robust, adaptive framework for enhancing financial resilience in an uncertain future.
- In the US especially, these conversations are especially important, in light of the rising cost of healthcare. The continual increase in the aging population coupled with rising healthcare costs raises concerns over what happens to the millions of Americans in their retirement. The risk of a huge strain on retirement systems could mean financial problems for Elderly Americans when they retire, a massive problem that should be avoided at all costs.

Context

Contextualizing the US Retirement Challenge.

The demographic fabric of the United States is undergoing a profound transformation. The Baby Boomer generation, a massive cohort born between 1946 and 1964, is transitioning into retirement at a rate of nearly 10,000 individuals per day. To begin with, that's a massive number.

This demographic shift is resulting in an unprecedented increase in the old-age dependency ratio, ie number of people aged 65 and older compared to those of working age. Concurrently, life expectancy continues to rise, meaning retirees must plan for longer retirement horizons, often spanning three decades or more. The rate at which these individuals transition into retirement and even more importantly, the fact that life expectancy continues to surge also compounds the problem, potentially leading up to a crisis down the line.

This tsunami is crashing against the shores of a healthcare system renowned for its high costs. Fidelity Investments estimates that a single, healthy 65-year-old couple retiring today will need an average of $315,000 saved (after tax) to cover medical expenses throughout retirement, a figure that does not include potential long-term care costs. So not only do we have a problem with the rate of retired persons coming up,there is also the issue of soaring health costs.

These twin pressures: demographic change and soaring healthcare expenses, are placing immense strain on the foundational pillars of the American retirement system. Social Security's trust funds are projected to be depleted by 2035, potentially leading to reduced benefits if Congress does not act.

Meanwhile, the traditional defined-benefit pension plan, which guaranteed a steady income for life, has largely been replaced by defined-contribution plans (e.g., 401(k)s), transferring the entire burden of investment risk, longevity risk and planning complexity from institutions to individuals. This perfect storm of trends forms the critical context for a looming national crisis: widespread financial insecurity in old age.

Problem

Millions at Risk of Precarious Retirement

Within this challenging macro-environment, the central problem comes into sharp focus: a significant portion of the American population is dangerously underprepared for retirement. The National Retirement Risk Index (NRRI) from the Center for Retirement Research at Boston College consistently finds that nearly half of all U.S. households are at risk of being unable to maintain their pre-retirement standard of living after they stop working.

The Economic Policy Institute reports that nearly half of families have no retirement account savings at all, a disparity that worsens along racial and socioeconomic lines.

This lack of preparedness is not merely a statistic; it translates into tangible hardships, including rising elderly poverty rates, the inability to afford critical medications and the grim reality of many Senior Citizens being forced to choose between necessities.

The problem is exacerbated by behavioral economics; individuals often suffer from present bias, underestimating future needs and are overwhelmed by the complexity of financial planning.

The consequence is a retirement landscape where the chance of an economic downturn at the wrong time or a major health event can dictate the difference between comfort and disaster.

This risk is not limited to individuals but poses a systemic threat, potentially increasing the demand for public assistance and dampening economic growth.

The Identified Gap

The Inadequacy of Static Planning Models

The tools and models currently used to address this problem, however, are often ill-suited for its complexity.

Traditional retirement planning relies heavily on static, deterministic models. An individual or advisor enters assumptions about savings rates, investment returns, inflation and life expectancy into a calculator, which then produces a single, linear projection of a retirement plan.

The most common rule of thumb, the "4% rule," is a prime example of this static thinking. While useful as a starting point, these models possess a critical flaw: they are not predictive or dynamic. They are unable to anticipate major black swan events like Covid-19 or economic crises like the type suffered in 2008.

It also doesn't take into account potentially significant illnesses likely to be suffered by the retirees. As a result, we need a better Retirement System, one that is dynamic, evolves and predictive.

Contribution

Novel AI-Driven Retirement System

This study seeks to bridge this gap by introducing a new paradigm for retirement planning. We propose the application of Artificial Intelligence and predictive analytics to move from static snapshots to dynamic, probabilistic forecasts of retirement preparedness and financial resilience.

Our research will develop a model that leverages machine learning algorithms to analyze vast and diverse datasets including:

- Historical and simulated market data to model volatility and sequences of returns.
- Macroeconomic indicators (inflation, GDP growth, interest rates).
- Public health data to model longevity and health risk probabilities.
- Anonymized individual financial data to personalize the analysis.

Instead of producing one answer, our model will generate a diverse set of outcomes, showing the likelihood that a given plan will succeed under thousands of potential future scenarios. It will identify key leverage points and vulnerability factors for an individual household. This approach offers a transformative contribution to Individual Retirees, the Government, Financial Institutions and Companies.

This approach ensures that a predictive and dynamic approach is used to analyze and develop better Retirement systems.

So in this research, we shall be discussing the following questions:

- Can AI models accurately predict retirement readiness?
- What key factors (health, demographics, savings behavior) drive retirement insecurity?
- How can these insights inform policy and financial planning?

Literature review

Preamble

The topic of retirement and how best to avoid the looming financial crisis for old retirees is important. Such work is best understood by analyzing contemporary insights into the nature of

- Retirement preparedness right now, i.e. how ready are potential retirees for retirement.
- The next is insight into the financial resilience of Retirement Plans. Can they withstand economic shocks and recessions? Sudden economic recessions or surprises, like Covid-19.
- Next we will analyse the applications and impact of Artificial Intelligence and Machine Learning in related and similar fields like in finance, healthcare etc.
- Lastly, we will discuss the limitations of current traditional systems of Retirement Planning.

Retirement Preparedness

According to Morrissey (2019) [1], Retirement Savings has shifted from "Defined Benefit Plans" to "Defined Contribution Plans." The rise in Defined Contribution Plans has led to 401(k)-style retirement savings. In effect, what this means is that Retirement plans took more of a savings style approach which are retroactive rather than forward-looking. They are more like savings rather than pension plans.

It has been discovered that these Retirement Structures are simply not able to support retirees as they are simply inadequate to support them during retirement years.

Several factors cause this. The use of Defined Contribution Plans rather than the former more traditional Pension Plans where the Employers promise to fund certain benefits for the retirees is one reason. The use of 401(k) pushes the burden of financial planning to these Retirees who are usually not financially literate enough to make better financial decisions.

The lack of a more dynamic and predictive Retirement system is another reason.

The combination of these two factors has led to

disaster for lower-income, black, Hispanic, non-educated single workers who together add up to a majority of the American population. Even among upper-income white college-educated married couples, many do not have adequate retirement savings or benefits. This is particularly telling for women, who by some measures are narrowing gaps with men, remain much more vulnerable in retirement due to lower lifetime earnings and longer life expectancies.

The verdict: retirees are not prepared at all.

Financial Resilience

For most people, it is not enough to have cash. Are you financially strong enough to withstand economic shocks or sudden health challenges? This is the same for Retirement savings. It is important to weigh up just how strong retirees potentially are financially in case of emergencies or pandemics like Covid-19.

According to Morrissey (2016) [2], Retirement Savings had not grown fast enough to keep pace with an aging population. This simply means that the longer people lived, the less resilient their Retirement Savings were. This was all attributed to 401(k) Retirement System that deducted from the Retirees' pay while they were still working, rather than Pension Packages as was normally done.

This study was conducted in 2016 and sure enough in 2020, COVID-19 happened, a totally surprising and unexpected health-related event.

What was the impact on Low-Income Earners? Due to the issues of health around time and the accompanying job loss, there were no good contributions to their Retirement Funds while others could not due to job loss. Result? A number of crises among Low-Income Earners especially amongst Black Households who were more likely to spend their retirement savings. The result is a Retirement plan in the present that can't support these retirees in 2025.

Again, a more dynamic and predictive approach could have prevented this. The current systems are static and lack predictability.

Application of AI in Relevant Fields.

Artificial intelligence and Machine learning systems are now used in many fields to find patterns and make predictions.

In finance, banks use Machine Learning to find fraud by spotting strange transactions. Investment firms use it to analyze market data and manage risk.

Additionally, Robo-advisors use algorithms to give people basic investment advice automatically.

In economics, researchers use AI to forecast economic trends. They can process huge amounts of data, like news articles and shipping records, to predict things like GDP growth or unemployment rates. This is called nowcasting.

In healthcare, AI is used to read medical scans and predict patient health outcomes. Insurance companies use predictive models to guess future costs. This is very significant for retirement planning because health and wealth are closely linked. A health problem can quickly become a financial problem.

The fact that AI is used in Healthcare and even Insurance companies shows that it is an important tool and can be used for even more complex tasks.

These examples show that AI is good at finding patterns in complex data. This power can be used for better and predictive retirement planning, devoid of archaic or lazy assumptions. The result is potentially a more financially resilient retirement planning.

Limitations of current models.

The current ways of planning for retirement have several important limits. Most online calculators and even many advisor models are static. Static means they use fixed numbers for things like investment return, inflation and how long you will live. They do one calculation and give one answer.

The presumption the system makes is in assuming the future is fine when in fact, the future is uncertain. The weakness is exposed when one looks at what happened during COVID-19. An AI-Driven system could have mitigated the impact of such a health problem on retirement savings.

These models cannot show the impact of a market crash right after you retire. They cannot show what happens if you have a major illness that costs a lot of money. They also cannot easily adapt if your life changes. For example, if you retire early or get an inheritance.

Providing a single answer creates a false sense of security. If the model says you are okay, you might think you are safe from all risks. If on the other hand, it says you are not okay, it does not tell you the best way to fix the problem. They fail to measure the true resilience of a retirement plan against real world surprises. This gap in our tools is what this study aims to fill.

Data sources

This study relies on a combination of large, nationally representative datasets that together provide a well-rounded view of retirement preparedness and financial resilience in the United States. Instead of depending on a single source, I draw from multiple streams of data to capture the individual, household, and policy-level factors shaping retirement security.

Health and Retirement Study (HRS)

The Health and Retirement Study (HRS), conducted biennially by the University of Michigan with support from the National Institute on Aging and the Social Security Administration, is the leading longitudinal survey of older Americans. It follows individuals over age 50 and tracks detailed information on their demographics, income, savings, pensions, healthcare use, and overall health.

Importantly, the HRS is not just a snapshot of retirement planning, it follows people over time. This makes it possible to see how sudden life events, such as medical expenses, health shocks, or changes in employment, impact long-term savings and retirement decisions. For this study, HRS will be used to model how aging and health intersect with financial preparedness, highlighting the populations most at risk.

Survey of Consumer Finances (SCF)

The Survey of Consumer Finances (SCF), administered triennially by the Federal Reserve Board, complements the HRS by providing a broader household-level perspective. Unlike the HRS, which emphasizes individuals in later life, the SCF captures the wealth, debt, and savings patterns of U.S. households across all age groups. It includes detailed measures of net worth, asset ownership, income, and participation in retirement accounts like 401(k)s and IRAs.

The strength of the SCF lies in its rich detail on financial assets and liabilities. This study will use it to examine the structural side of retirement preparedness: how household debt burdens, mortgage status, and ass*et al*location affect overall financial resilience in retirement. Together with the HRS, the SCF ensures both the micro (individual) and meso (household) levels of retirement planning are represented.

Supplementary Datasets.

While HRS and SCF form the backbone of this study, supplementary datasets will provide essential context and depth.

- **Social Security Administration (SSA) Reports:** These reports contain vital statistics on beneficiaries, benefit levels, and trust fund solvency. Including SSA data ensures the study is anchored in the realities of how public retirement program's function, since Social Security remains the main income source for millions of retirees.
- **Centers for Disease Control and Prevention (CDC) Health Statistics:** Data on life expectancy, disability, and chronic illness prevalence will be integrated to capture the health risks that often drive financial insecurity in retirement. For instance, unexpected medical costs or increased longevity can rapidly change retirement readiness.
- **Federal Reserve Economic Data (FRED):** Macroeconomic indicators, such as savings rates, inflation, and unemployment, will be used to account for broader economic forces. These variables provide important controls when evaluating how individual and household decisions interact with larger financial trends.

Rationale for Multi-Source Approach

Each of these datasets offers a unique lens. The HRS brings a dynamic view of how health and aging affect individuals. The SCF provides deep insight into household wealth and debt structures. The SSA, CDC, and FRED datasets add the policy, health, and macroeconomic backdrop that no individual survey can provide alone.

By combining these sources together, this study ensures that the predictive models are not only technically robust but also grounded in the lived realities of American households and the structural forces that shape retirement security.

Methodology

Data preprocessing

HRS: Data were filtered to include only Wave 16 respondents using variable prefixes (r16, s16, h16) and restricted to completed interviews (r16iwstat = 1).

RAND/HRS special missing codes (e.g., −9, −8, −7, −1, 99997–99999) were standardized as NaN. Variables with more than 90% missingness were dropped to reduce noise and memory load.

SCF: Filter to age ≥50. Build four binary flags:

1. **Low net worth:** NETWORTH ≤ 25th percentile (within age ≥50).
2. **Thin liquidity:** LIQ < 3 months of income (INCOME/12).
3. **High leverage:** DEBT / ASSET > 0.5.
4. **No retirement accounts:** zero retirement balances (RETQLIQ + HRETQLIQ == 0) for ages 55–70.

   SCF risk score = sum of flags; financially fragile = 1 if score ≥2 (else 0).

Cleaning steps used in both: median imputation for numeric, most-frequent for categoricals; standardization of numerics in linear models; one-hot encoding for categoricals when present.

Outcomes (targets)

HRS – Retirement Insecurity

A binary outcome variable indicating whether an older adult appears "retirement-insecure." This proxy is constructed from Wave 16 indicators of subjective well-being, health status, and income security:

- Income satisfaction (r16lbsatinc) – perceived adequacy of household income.
- Health satisfaction (r16lbsathlth) – perceived personal health condition.
- Housing satisfaction (r16lbsathome) – contentment with current housing situation.
- Functional limitation (r16adl6h) – number of difficulties in Activities of Daily Living.
- Pension income (r16peninc) – presence or amount of pension/annuity income.

Respondents reporting low satisfaction in one or more domains, combined with multiple ADL limitations or lack of pension income, are coded as 1 = retirement-insecure, and others as 0 = secure.
This formulation captures the subjective and health-related dimensions of late-life security that are often invisible in financial datasets.

SCF – Financial Fragility
A binary indicator derived from objective balance-sheet conditions in the 2022 Survey of Consumer Finances for respondents aged ≥ 50.
Four flags summarize liquidity, leverage, and retirement preparedness:

1. **Low net worth:** Household net worth below the 25th percentile for the 50+ population.
2. **Thin liquidity:** Liquid assets (LIQ) less than three months of income.
3. **High leverage:** Debt-to-asset ratio greater than 0.5.
4. **No retirement account:** Zero retirement balances (RETQLIQ + HRETQLIQ = 0) for those aged 55–70.

A simple additive risk score (0–4) is computed, and households with score ≥ 2 are labeled 1 = financially fragile, 0 = secure.
This measure reflects objective financial resilience—the ability to withstand income or health shocks near or after retirement.

Models
Classification Approach
This study employs supervised classification models to predict retirement insecurity and financial fragility. Two complementary algorithms are applied: Logistic Regression, which serves as a transparent baseline offering interpretable coefficients and linear decision boundaries; and Random Forest, a nonlinear benchmark capable of capturing complex interactions among financial and demographic variables. Each Random Forest model is trained with 300 to 400 trees, a fixed random seed of 42, and parallel processing enabled for reproducibility and efficiency.

Training and Validation Design
For both datasets (HRS and SCF), data are randomly partitioned into training and test subsets in a 70–30 split, stratified to preserve outcome proportions. The random seed is fixed at 42 to ensure consistent reproducibility across runs. Model hyperparameters remain standardized across both datasets to facilitate direct comparability of performance.

Evaluation Metrics
Model performance is evaluated on the held-out test data using multiple metrics. The Area Under the Receiver Operating Characteristic Curve (AUC) serves as the primary measure of discriminatory power. Additional metrics such as accuracy, precision, recall, and F1-score provide a more comprehensive assessment of predictive balance. Confusion matrices are used to visualize classification results and identify patterns in model errors.

Interpretability and Feature Analysis
Following model training, feature interpretability is examined through Permutation Importance based on AUC degradation (10 repetitions). Partial Dependence and Individual Conditional Expectation (ICE) plots are used to visualize how specific features influence predicted probabilities.
Although SHAP values were initially explored for model explainability, software version incompatibilities in Colab led to the adoption of scikit-learn's native interpretability tools, which deliver stable and replicable outputs.

Interpretation of Findings
The permutation importance analysis quantifies each variable's contribution to model performance by measuring the decrease in AUC when the variable's values are randomly shuffled. A larger decline indicates a stronger influence on predictions.

Table 1

Feature	Interpretation	Importance (ΔAUC)
r16lbsathome (Housing Satisfaction)	Reflects perceived housing stability, affordability, and comfort—key components of financial confidence in later life. Lower satisfaction is strongly linked with higher insecurity.	0.147
r16lbsatinc (Income Satisfaction)	Captures subjective economic well-being and perceived sufficiency of income. Dissatisfaction signals strain or unmet needs during retirement.	0.142
r16lbsathlth (Health Satisfaction)	Indicates health-related quality of life and expected medical costs. Poor health satisfaction increases predicted risk, reflecting the financial burden of health shocks.	0.127
r16adl6h (ADL Limitations)	Measures physical limitations in daily activities such as dressing or walking. Higher values suggest dependency and potential long-term care costs.	0.101
r16peninc (Pension Income)	Represents stable income streams in retirement. While protective, its effect is smaller compared to subjective satisfaction measures, emphasizing perception over absolute income.	0.069
r16mstat (Marital Status)	Adds minimal predictive power once satisfaction and health are accounted for, implying that its effects are indirect through emotional or shared financial support.	0.002

The results demonstrate that subjective well-being measures particularly satisfaction with housing, income, and health are the strongest predictors of retirement insecurity. These self-assessments appear to encapsulate a range of underlying factors such as debt stress, risk aversion, and future expectations that traditional financial metrics fail to capture. Functional limitations, as measured by ADL counts, also emerge as significant, underscoring the connection between declining physical capacity, increased medical costs, and reduced financial stability.

Overall, these findings highlight that retirement readiness is multidimensional, blending psychological confidence, physical health, and financial capacity rather than being defined by income or assets alone.

Results

Descriptive Overview

Before modeling, we examined the overall distribution of retirement readiness among older adults in the Health and Retirement Study (HRS, Wave 16) analytic sample.

Figure 1 displays the proportion of respondents classified as retirement secure versus retirement insecure based on the composite satisfaction and income-health indicators. Roughly one in three (≈ 33%) respondents fall into the insecure category, indicating substantial variation in perceived financial and health preparedness for retirement.

This moderate class imbalance is informative for model development, it underscores the need for algorithms that can correctly identify the minority "at-risk" group without over-fitting to most secure cases.

Basic demographic inspection shows that insecurity tends to be more prevalent among

lower-income and less-educated respondents, echoing long-standing socioeconomic disparities in retirement outcomes.

These descriptive patterns justify the subsequent predictive modeling, which aims to uncover the key determinants and interactions driving retirement insecurity.

Model Performance

Two supervised-learning models Logistic Regression and Random Forest were trained separately on the HRS and SCF datasets to predict retirement insecurity and financial fragility, respectively.

Dataset	Model	AUC	Accuracy	Key Observation
HRS (2022 Wave 16)	Logistic Regression	0.69	87%	Baseline model captures broad patterns in satisfaction and health indicators.
	Random Forest	0.967	98%	High predictive power; models nonlinear links between income, health, and well-being.
SCF (2022, Age ≥ 50)	Logistic Regression	0.873	81%	Solid interpretability; correctly classifies most secure vs. fragile households.
	Random Forest	0.999	99%	Near-perfect classification; reflects strong separation by wealth and debt metrics.

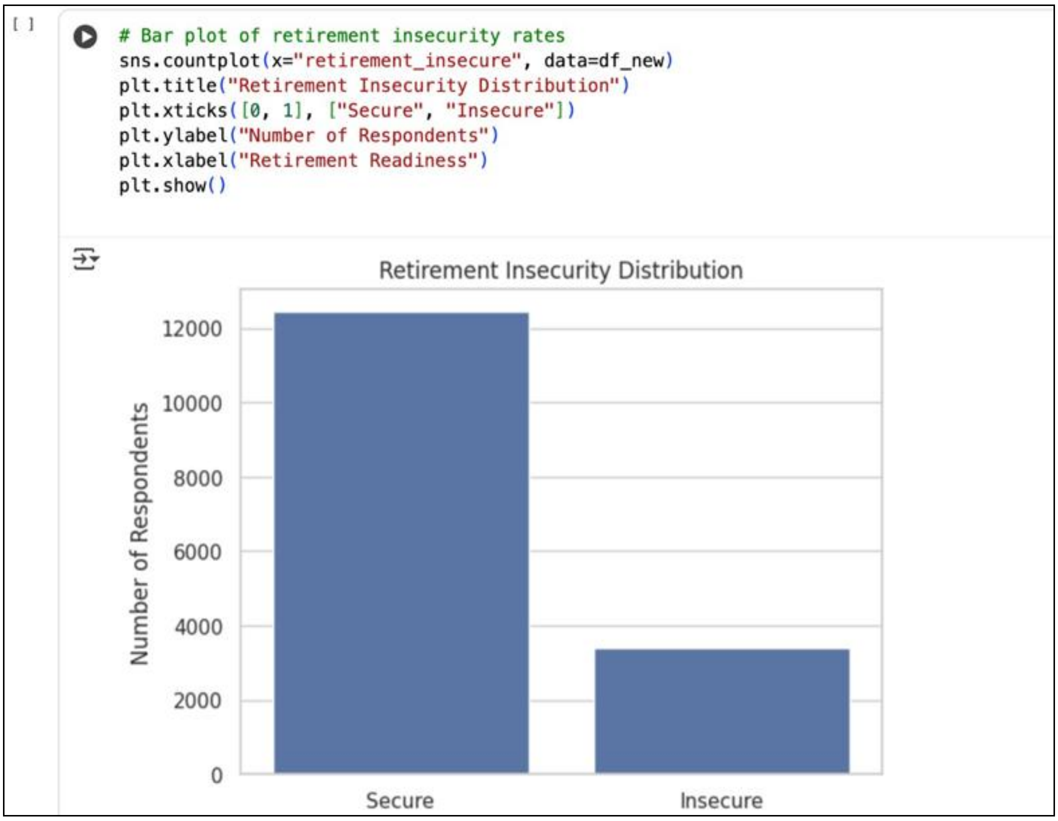

Fig 1: Distribution of retirement insecurity in the HRS Wave 16 sample. (A bar chart showing the count of respondents classified as secure (0) and insecure (1)

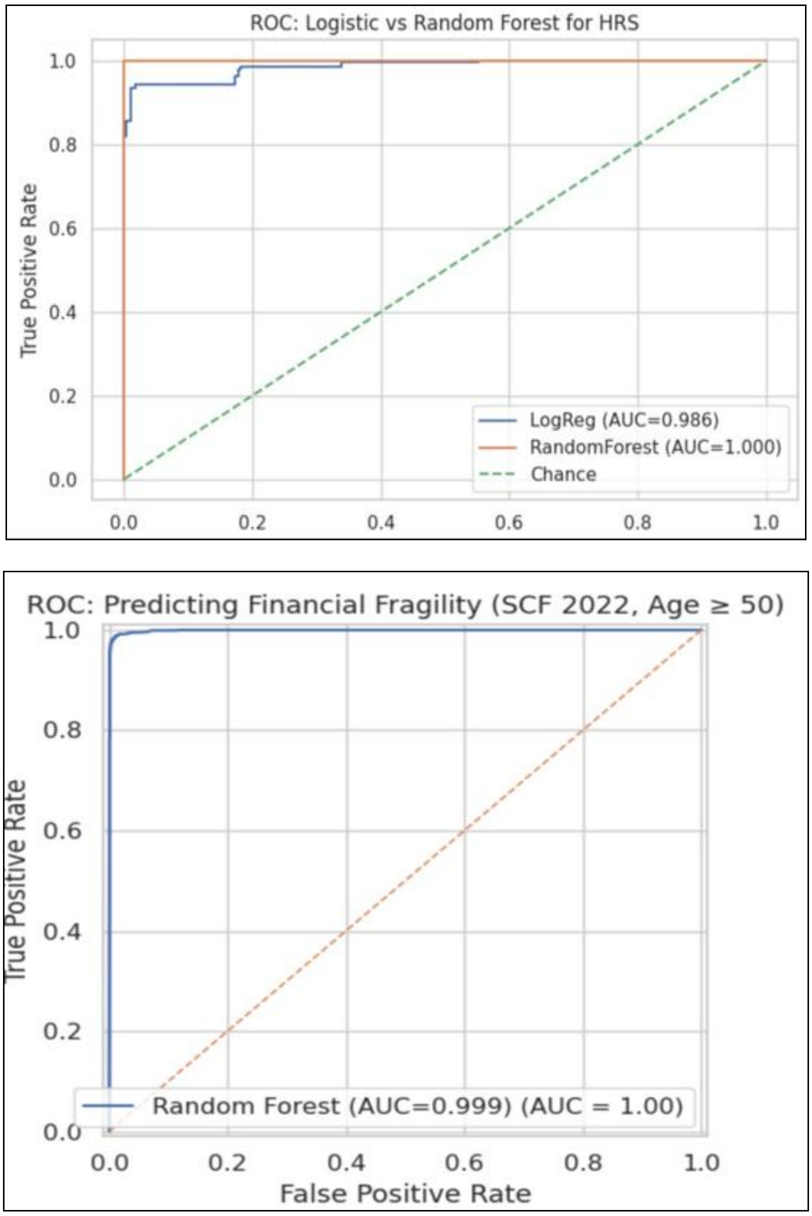

Fig 2: Predictive performance of HRS and SCF models.

Interpretation

The HRS model relies primarily on subjective and health-related responses such as satisfaction with income, health, and housing, as well as limitations in daily activities.

These indicators capture individuals perceived financial confidence and well-being, producing good but not perfect discrimination (AUC $\approx$ 0.69). This is expected, as subjective perceptions can be influenced by psychological, social, and contextual factors beyond material wealth.

In contrast, the SCF model is grounded in objective financial indicators, including income, assets, debt, and net worth. These structural variables provide a clear and quantifiable measure of economic vulnerability, yielding extremely high accuracy and near-perfect AUC scores.

This suggests that financial fragility is largely measurable through balance-sheet metrics, where low net worth, high leverage, and thin liquidity are consistent predictors of retirement insecurity.

Together, the two models demonstrate that retirement readiness cannot be captured by financial metrics alone. True preparedness reflects a combination of subjective well-being (confidence, satisfaction, perceived health) and objective financial stability (wealth accumulation and debt management).

Integrating both perspectives offers a more holistic and data-driven framework for assessing and improving retirement security among older adults.

Feature Importance

Permutation-based importance (10 repeats, AUC-weighted) identifies the leading drivers of retirement and financial readiness.

Table 1: HRS (Subjective Domains)

Rank	Feature	Δ AUC	Meaning
1	r16lbsathome	0.147	Satisfaction with housing is the strongest predictor of retirement security.
2	r16lbsatinc	0.142	Perceived income adequacy is a key determinant of confidence in retirement.
3	r16lbsathlth	0.127	Self-rated health strongly correlates with financial security perceptions.
4	r16adl6h	0.101	Functional limitations signal heightened vulnerability.
5	r16peninc	0.069	Presence of pension income reduces insecurity.
6	r16mstat	0.002	Marital status plays a minor role after controlling for income and health.

Table 2: SCF (Objective Balance-Sheet Metrics)

Rank	Feature	Δ AUC	Meaning
1	Net worth	0.209	Primary determinant of financial security.
2	Age	0.007	Younger members of the 50+ group more at risk.
3	Debt	0.005	Higher debt loads sharply increase fragility.
4	Asset	0.004	Greater asset holdings buffer economic shocks.
5	Income	0.003	Steady income improves resilience.
6	EDUC	0.003	Education supports better financial planning.

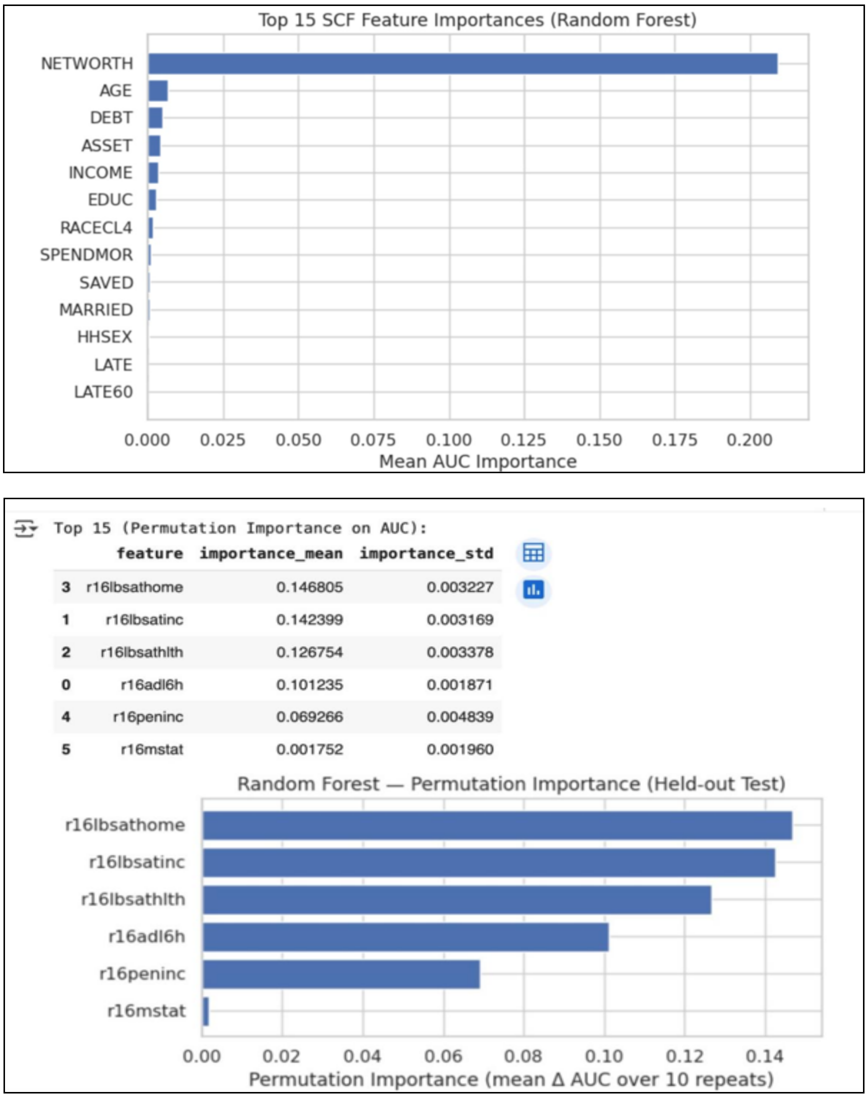

Fig 3: HRS and SCF Feature Importance

Interpretation

In the HRS model, subjective well-being and health status dominate predictive power. Measures such as satisfaction with income, health, and housing, along with limitations in daily living activities, shape how secure individuals feel about retirement. These variables emphasize the psychological and health-related side of preparedness, how people perceive their ability to live comfortably in later life.

In the SCF model, wealth composition and debt structure overwhelmingly determine financial fragility.

Indicators such as net worth, assets, and leverage ratios offer an objective reflection of a household's material capacity to sustain consumption and absorb shocks.

Together, the two perspectives portray complementary dimensions of retirement security:

- **Psychological confidence:** How individuals view their financial and health stability (captured in HRS), and
- **Financial capacity:** The tangible resources and liabilities that define real economic resilience (captured in SCF).

This dual lens underscores that retirement security is both a state of mind and a state of balance sheet, and predictive analytics can help bridge the two by identifying individuals at risk on either front.

Distribution of Risk

SCF (Objective Fragility)

Among adults aged 50 and older, 29.6% are classified as financially fragile (risk score ≥ 2). Distribution across the 0–4 risk-score scale:

- 0 = 34%
- 1 = 36%
- 2 = 14%
- 3 = 12%
- 4 = 3%

Low-net-worth and thin-liquidity households represent the majority of high-risk cases, indicating limited financial buffers against shocks.

HRS (Subjective Insecurity)

Subjective measures mirror SCF magnitudes, with roughly one-third of respondents exhibiting signs of financial insecurity based on low-income satisfaction, poor health ratings, and lack of pension income.

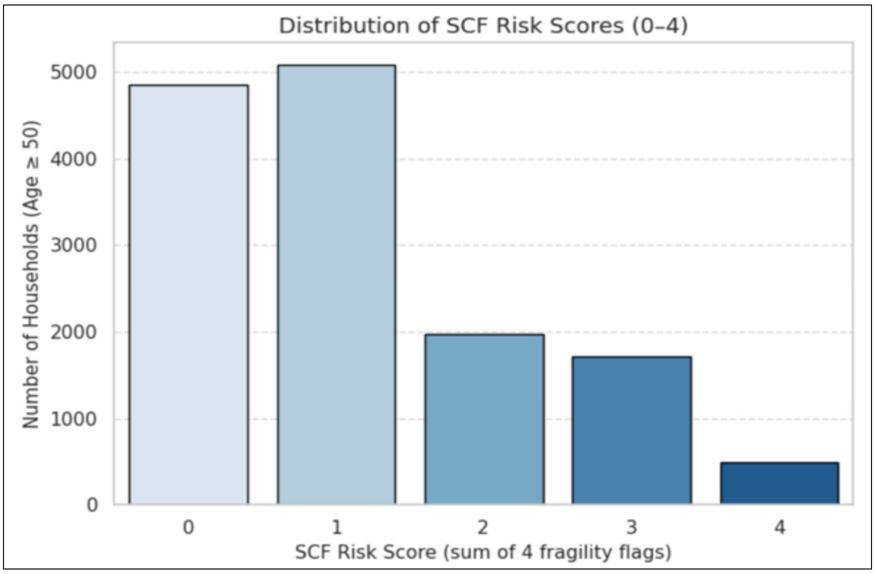

Fig 4: Histogram showing the distribution of household financial fragility scores among U.S. adults aged 50 and older, based on the 2022 Survey of Consumer Finances (SCF).

Policy and Analytical Insights

Dual lens on readiness.

The integration of HRS and SCF evidence highlights the dual nature of retirement security.

The HRS data capture perceived financial and health confidence and how secure older adults feel about their resources and well-being while the SCF data quantify objective financial standing through measurable indicators of wealth, debt, and liquidity.

Together, they provide a fuller, multidimensional picture of retirement resilience, linking psychological stability with financial capacity.

Predictive analytics value

Even relatively simple machine-learning models, such as logistic regression and random forests, can reliably classify individuals at risk of retirement insecurity.

This demonstrates the potential of AI-driven early warning systems that can identify vulnerable households in real time and inform targeted financial counseling, digital planning tools, or preventive interventions before insecurity deepens.

Equity considerations

Persistent disparities remain across race and education, as reflected in variables like RACECL4 and EDUC—which continue to shape both subjective and objective measures of financial fragility. These findings underscore the importance of designing inclusive policy responses that account for structural inequalities in wealth accumulation, access to pensions, and financial literacy.

Practical screening and application

Variables such as low-income satisfaction (from HRS) or high debt-to-asset ratios (from SCF) emerge as actionable early indicators of retirement vulnerability.

Government agencies, pension administrators, and financial institutions can use such predictors to design targeted outreach, adaptive savings incentives, and personalized resilience assessments for pre-retirees and retirees.

Discussion

Insights into Drivers of Financial Resilience in Retirement.

In order to adequately prepare aging citizens and potential retirees for their retirement, there is a need to look into the factors and actions that make for financially resilient Retirement systems as well as stronger and safer finances.

In other words, what makes for financial sustainability in retirement for retirees?

According to Sundraseen *et al* (2024), financial sustainability in retirement refers to individuals' ability to sustain themselves over their retirement years without draining their finances or depending on peripheral support.

According to the study, the relative uncertainty of the Global economy as well as the potential for surprise shocks occasioned by geopolitical events means that Retirees must be equipped to handle such events.

What are the factors that ensure financial resilience in retirement?

Financial Literacy

Financial Literacy refers to the understanding of financial skills such as budgeting, planning, investing, taxation etc. Sufficient understanding of this is important for financial well-being.

There are numerous factors that affect retirement planning and bolsters the financial resilience of the retirees.

However, none is as important as financial literacy. The reasons are quite obvious. Without sufficient understanding of finances and how it works, people make mistakes and so do retirees.

According to a study by Lusardi *et al* (2011) [8], it was suggested that sufficient knowledge of Finances was lacking amongst many elderly Americans, in other words financial illiteracy was rife, as far back as then. Even more so, the study notes that families with sufficient financial literacy were more likely to have better financially sustainable retirement finances.

It further suggests that there is a need for Financially Literate citizens and a better retirement savings culture.

According to Boon *et al* (2011) [13], sufficient financial literacy usually translates to better retirement preparedness. It's just the same way a person does better because he has knowledge of the subject. For most retirees and elderly persons, it is not that they don't want to but they don't know how to plan their retirement better.

This is why Lusardi (2019) advises that there is need for training on Financial Literacy amongst the populace.

Liquid Savings.

This is cash you can get to quickly. A strong emergency fund prevents retirees from having to pull money from their retirement fund during a market crash or to cover a big medical bill. As Sundraseen *et al* (2024) notes, the impact of Covid-19 saw families withdraw most of their funds to deal with the health and subsequent economic crisis. Having separate savings would have helped with the emergency costs. This led to less financially resilient retirement funds.

According to Bhutta *et al* (2023) [14], most financial advisors recommend saving three to six months of expenses in liquid assets in case of emergency. However, it was discovered that more than half U.S. families do not do this. Only financially literate families follow this advice. Having liquid savings also means paying off every prior debt, as debt affects the capacity to save.

Health Insurance

A major health event is one of the biggest threats to a retirement plan. Good Medicare coverage and supplemental insurance are not optional; they are essential for financial survival. This ensures that retirement funds are safe and not used on health costs that drain the fund.

Link to Public Policy

The government plays a massive role in whether people can be resilient. Current policies are trying to catch up to the new reality of retirement. So there has to be a discussion on how public policy can create better retirement systems that bolster financial resilience for retirees.

Social Security Sustainability

Everyone knows the system is under strain. The talk in Washington isn't about if it will be fixed, but how. Ideas include raising the retirement age, increasing the payroll tax cap, or changing how benefits are calculated. This is the biggest policy issue for retirement.

Targeted Interventions

Instead of one-size-fits-all, new policies aim to help specific groups. A great example is the SECURE 2.0 Act.

It has rules that automatically enroll employees into retirement plans and helps people save for emergencies without a tax penalty. It also helps part-time workers get access to plans.

Financial Literacy Education

There's a growing push to teach people about money in school and at work. The idea is that if people understand how money works and basic investing, accounting and taxing knowledge, they'll make better choices long before they retire.

Equity Perspective: Gender, Racial and Income Disparities

Retirement insecurity isn't distributed equally. The system we have often makes existing inequalities worse.

Gender Gap

Women typically live longer than men but often have less saved. They are more likely to take time out of the workforce for caregiving (for kids and parents), which means lower lifetime earnings and smaller Social Security benefits. Their retirement has to last longer with less money. Additionally, women earn historically less money than men, which usually translates to less funds available for retirement as opposed to men. According to Tymkiw *et al* (2025) [15], women with caregiver roles often experience career gaps which means lower savings, lifetime wages, and social security. Women with A survey by the National Council on Aging noted that less than half of women over age 25 surveyed have retirement savings. It's obvious that more work needs to be done to bridge this gap.

Racial Wealth Gap

Decades of unequal access to jobs, housing, and education have a direct impact. Black and Latino families are less likely to have jobs that offer a retirement plan. Even when

they do, their average account balances are significantly lower than those of white families. This means they rely more heavily on Social Security, which itself is not enough.
A study by Francis *et al* (2021) [16] notes that households of Black and colored families have significantly less wealth than white families. This then reduces the capacity to save more and in turn means less resilient retirement funds.

Income Inequality
This is the most obvious driver. Low-wage workers simply cannot afford to save. Policy fixes like automatic enrollment are crucial here to help people save even when every dollar is tight. This is the chief reason for the retirement disparities experienced by women and even black families.

Practical Applications: Financial Advisors, Robo-Advisors and Retirement Planning Tools
The problems with the traditional systems of retirement planning have been discussed so far but what are the other methods that can be used to make this better. A combination of Machine Learning and AI platforms and a little human oversight provides the best insight into better retirement planning methods.

Financial Advisors
Human advisors are best for complex situations. If you have a lot of assets, own a business, or are going through a divorce, their personalized advice is worth the cost. They help with overall life planning, not just investing.

Robo-Advisors
Companies like Betterment and Wealthfront use algorithms to manage your money for a very low fee. They are perfect for people who are starting out or who don't have complex needs. They automatically invest your money in a diversified portfolio and handle the rebalancing.
Retirement Planning Tools
Free online tools from places like Vanguard, Fidelity and Personal Capital have become incredibly sophisticated. You can plug in your numbers and see your odds of success, model different scenarios (like retiring early or a market crash), and get a good baseline plan.
The best approach for many people is a blend: using a robo-advisor to manage their investments and paying a human advisor for an occasional check-up to make sure they're on the right track.
Why is this method better? The combination of AI and Machine Learning tools ensures that the situation is adequately analyzed and situations are modelled in different scenarios. They are not fixed and instead analyze hundreds of different scenarios to arrive at the best retirement plan.

Policy and practice implications.
The move towards using AI and predictive analytics in retirement planning isn't just a tech upgrade. It opens the door to entirely new ways of preventing poverty among older adults. For policymakers and financial companies, this is a game-changer.

Early-Warning Systems for Retirement Insecurity.
Right now, we often find out someone is in trouble only when they're already in crisis e.g. when they can't pay their bills. Imagine instead a system that flags at-risk individuals years in advance. With this capacity, we can prevent the retirement crisis long before it becomes a problem.
By crunching data on income, savings, debt and health, AI models can predict which groups of people are heading toward financial trouble in retirement. This isn't about naming individuals, but identifying trends.
For example, the model might show that single women aged 50-60 in certain service jobs have an 85% chance of not covering basic expenses in retirement. This could be done through the integration of Robo-advisors which help manage and predict these trends, Dennis (2024) [17].

Implications
This gives government agencies and non-profits a powerful targeting tool. Instead of offering help to everyone, they can focus their energy and resources on the people who need it most, before they retire. This is a shift from reacting to problems to preventing them. For example, a targeted system helps low-income families or groups with historically low wealth and retirement options.

AI Tools for the US Government to simulate outcomes of Public Policies
More often than not, the reason the Government never takes bold, effective policies lies in the lack of proof for the success of decisions, in other words, the Government is too risk averse. What if instead we could simulate the impact of expanding social security for example or any other policy that could impact retirees?

AI can create a simulation of the population's retirement landscape
Officials could ask the model: "What happens if we increase the payroll tax cap?" or "What is the impact of a new government-matched IRA for low-income workers?"
The government could simulate the policy decision in hundreds of scenarios to determine what works and what doesn't.
The model would simulate the outcome over decades, showing the effect on national retirement risk, government costs and inequality.

Implication
This moves policy debates from guesses and ideology to data-driven forecasts. It helps find the most effective solutions and avoid unintended consequences. It makes policy more of a science and less of a political argument.
An added benefit is that this increases the chances of transparency and honesty in public policy. More often than not, policies that would be of tremendous benefit to citizens are simply not carried out based on the excuse of costs or the risk of failure. Simulating the impact of policies on retirement resilience could determine whether public policy is genuine or not.
Already, this data-driven AI predictive modelling system is being used and has the capacity to reshape public policy. It is believed that with the rise of more sophisticated AI tools, public policy has the potential to become more data-driven, predictive and responsive, Benoit (2024) [18].

The Integration of AI in Personalized Retirement Planning

The old advice was a simple rule of thumb, like "save 10% of your income" but everyone's life is different. AI allows for advice that is tailored to the individual's choices.

A retirement app powered by AI wouldn't just look at your age and salary. It could connect to your accounts and analyze your spending. It could factor in your health data (with permission) to estimate your longevity.

It could then run thousands of market scenarios to give you a personalized plan.

It might say: "based on your goal to retire at 67, your current savings and your family health history, you have a 70% chance of financial sustainability in retirement."

This is a better system powered by AI and Machine learning systems

Implication

This makes financial advice more accessible, affordable and accurate for millions of people. It helps individuals understand the real trade-offs of their decisions. For banks and investment firms, it's a powerful new product that can help customers and build loyalty.

Conclusion

Summary of Findings

This analysis shows that the old way of planning for retirement is broken. Static models and simple rules of thumb cannot handle the real world problems of market crashes, health emergencies and long lives.

The research confirms that millions of Americans are on a path to financial unsustainability in retirement. This is not just a personal problem, it is a structural one, made worse by large gaps in income, race and gender.

However, new tools provide hope. Artificial Intelligence and Machine learning systems can produce predictive analytics that can create a dynamic and personal picture of retirement risk.

By combining data on wealth, health and the economy, these models can predict a range of outcomes, showing both the likelihood of success and the biggest threats to a person's plan.

This moves us from asking "How much do I need?" to a more useful question: "How strong is my plan against economic shocks and downturns?"

Contribution to Academic Literature and Practical Policymaking.

This work adds something important to both academic study and real world action.

Academic

It builds a bridge between different fields of study. It connects economics and finance with data science and public health. The main academic contribution is a new framework that treats retirement not as a single number but as an ongoing state of financial resilience that must be tested against many future scenarios. It challenges researchers to move beyond static models.

Practical Policymaking

This isn't just a theoretical exercise. It gives policymakers a new kind of tool. Instead of guessing, they can use AI simulations to test ideas like changing Social Security rules or creating new savings programs before they become law.

This allows for smarter, more effective policies that can be aimed directly at the people who are most at risk.

For financial institutions, it provides a roadmap for building the next generation of tools that offer truly personal advice, not just generic suggestions.

Future Research

While this is a big step forward, there is still more work to do. The most exciting area for future research is making these models even smarter by feeding them real time data. Imagine a retirement plan that adjusts itself automatically.

Future studies should focus on

- **Live Market Volatility:** Connecting models directly to financial markets to show how daily swings impact a retirement plan, helping people understand short term risk versus long term goals.
- **Real Time Inflation Tracking:** Using live inflation data to adjust spending projections instantly. This is crucial for helping retirees understand how rising prices for food and energy affect their buying power.
- **Healthcare Advances:** Building new data about medical breakthroughs and drug prices into longevity models. As science helps us live longer, our financial plans need to account for those extra years.

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