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Predicting Retirement Outcome Sufficiency with behavior-Aware ML: A Comparative Study of Contribution Nudges and Glide-Path Adjustments

Angela Matope [1, *], Munashe Naphtali Mupa [2], Grayton Tendayi Madzinga [2], Judith Saungweme [3], Tracey Homwe [4] and Kwame Ofori Boakye [5]

[1] Drexel University.
[2] Hult International Business School.
[3] Central Michigan University.
[4] La Salle University.
[5] Park University.
Angela Matope, ORCiD: 0009-0008-7503-5669
Munashe Naphtali Mupa, ORCiD: 0000-0003-3509-867X
Judith Saungweme, ORCiD: 0009-0006-6644-9419
Tracey Homwe, ORCiD: 0009-0005-9459-0199
Kwame Ofori Boakye, ORCiD: 0009-0004-3991-312X

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Abstract

Retirement planning is an issue that majority of the population especially the low and middle-income earners are worried about and there is no better time than now to establish viable and dynamic solutions that will see to it that the sufficient retirement is realized. Most of the traditional retirement savings plans like target-date funds (TDFs) employ the traditional glide-path plans to minimize risk in investing as the retiree approaches the retirement age. Of course, these strategies are effective in some cases, however they do not usually take into account instability of income and the non-standard conditions of individuals with variable income. This disparity is observed especially in the group of lower and middle-income earners who are more vulnerable to various economic recessions like loss of employment or medical accidents. Thus, there can be certain serious inconsistencies of these groups being willing to retire despite saving on a regular basis.

New developments in machine learning (ML) and artificial intelligence (AI) offer an opportunity to change the way retirement planning is done and make it more personal and dynamic. The retirement plans will also be more responsive to the changes in the income and will be customized to the needs of each individual saver with the assistance of these technologies. Examples of cases where AI and ML-based solutions are applicable include dynamically adjusting the contribution rates in response to changes in income or dynamically rebalancing investment portfolios in response to changes in income. Such adaptive plans can increase the retirement sufficiency of people with unpredictable financial journeys, but little empirical study has been carried out to contrast the effectiveness of traditional glide-path plans with AI-driven, behavior-conscious nudging.

Keywords: Comparative; Machine Learning; Nudges; Retirement

* Corresponding author: Angela Matope

1. Introduction

The purpose of this paper is to explore how traditional glide-path policies and AI-nudged policies can improve the retirement adequacy of lower- and middle-income savers. The comparison will be based on the way each strategy deals with major issues, such as income volatility and the threat of poor drawdowns at the retirement age. The paper uses a microsimulation model to model the effects of income shocks and evaluates how different nudges can be used to increase the savings rate and decrease risk exposure. In addition, methods of causal inference and reinforcement learning (RL) are used to assess the dynamically informed adjustments, that seek to enhance the alignment between retirement contributions and investment plans and individual income trends, as implemented by AI.

Despite the extensive use of AI and machine learning in other spheres of life, e-commerce and insurance risk management, they have not been studied in retirement planning. The potential of AI in predictive analytics and risk assessment is emphasized by the previous studies (Mupa et al., 2025), which state that it might be suitable to enhance retirement savings schemes. The purpose of this paper is to provide policy recommendations to policymakers and financial planners, in this instance those operating with state and local retirement plans with the perspective of enhancing the performance of underserved populations. The study can be used in the formulation of more effective policies to apply in the global public retirement system as it compares the traditional glide-path policies with the policies that are founded on AI.

2. Literature Review

2.1. Savings Behavior Retirement Planning.

Retirement benefits form an irreplaceable part of the financial planning and retirement adequacy is a significant challenge to many people, especially the low-income and middle-income earners. One of the most significant challenges is income volatility because these people find it difficult to contribute to retirement accounts on a regular basis in the long term. According to the existing literature, the traditional forms of retirement, such as the employer-sponsored retirement plans and target-date funds (TDFs), do not seem to provide enough solutions to this cohort of individuals since they are typically based on the overall incomes of the participants, which are predictable and consistent (Cobblah,2025). Unpredictability of incomes influences the ability of a person to save enough money and leads to unfavorable retirement results. What complicates this issue further, is that individuals are likely to procrastinate, underestimate the future, or present bias, where the urge to eat something now overshadows the need to save it to eat later (Mupa et al., 2025). These kinds of behavior patterns result in low savings towards retirement especially when individuals face unpredictable financial situations. Despite the fact that adaptive solutions are highly required, little focus has been on integrating behavioral knowledge with retirement planning, which puts most individuals at the risk of inadequate retirement savings.

2.2. Glide-Path Stratagem of Retirement Planning.

Target-date funds utilize glide-path strategies, which will lower the risk of investment with time as one approach retirement age. The modified approach is typical, in which, as a retirement date approaches, there is a shift to less risky (bonds or cash equivalents) to riskier (stocks) assets. Nevertheless, this strategy is feasible to those who have a stable income and can comfortably forecast their financial performance, taking into account the less predictable requirements of low-income and middle-income earners, including income fluctuations or economic crises (Nkomo & Mupa, 2024). Common glide paths are founded on a constant contribution rate and a constant increase of account balances over time, yet they do not take into account the reality that income levels can actually vary and that there can be urgent financial needs that require the early withdrawal of funds. By so doing, a number of individuals who are less well-off will be subjected to the threat of depleting their pension funds before they retire or contributing insufficiently to reach their retirement goals. Despite the fact that glide-path strategies have received a lot of research and implementation in the retirement planning field, the inability to address the needs of more vulnerable groups, especially workers with income instability, has led to the development of alternative strategies. These groups would receive better retirement results in more personalized remedy that would take into account their own financial situations.

2.3. Nudges in Retirement Savings.

The use of behavioral science in the retirement plans has become popular as a possible method of enhancing the performance of the savings. Behavioral nudges are any interventions that encourage the decision maker to make a better financial decision but do not restrict their freedom to make free choices. The retirement scheme automatic enrolment or automatic increases of the contribution amounts of a scheme are examples of schemes that encourage people to make a greater contribution without the necessity of participating (Mupa et al., 2025). These measures have been established to increase the degree of involvement and contribution towards savings especially to those individuals who might not be keen on saving and investing in the future. The effectiveness of behavioral nudges lies in the fact that they reduce the prevalent level of cognitive bias, including the tendency to procrastinate or the lack of knowledge to plan their long-term objectives properly. Even low- to middle-income individuals can become much more retirement ready with the help of nudges, such as default saving rates or automatic adjustments based on income. Nevertheless, their use in the context of retirement planning is not researched in detail, especially in dynamic and real-time environments, since the literature on their effectiveness in terms of impacting individual behavior is widespread in other fields, such as the sphere of e-commerce (Nkomo & Mupa, 2024).

2.4. Artificial Intelligence and Machine Learning in Financial Decision-Making

The latest advances of artificial intelligence (AI) and machine learning (ML) may provide efficient approaches to retirement planning improvement. The machine learning algorithms can be used to process large volumes of financial data to forecast the future income curve, financial needs and risks of an individual and optimize the retirement plans to match them with the trends (Tiwar et al.,2024). It benefits those who have variable incomes since AI will have the capability to adjust the saving plans on a case-by-case basis to propose the optimal contribution or redistribute the funds based on the expected changes in income and market factors. When it comes to retirement planning, the additional data point, including spending habits, life aspirations, and health risks, might be considered to provide higher levels of personalized guidance, which is based on AI-driven financial products.

AI and big data have been used in risk management, such as in liquidity risk management in financial services which has been useful in enhancing the data-driven and context-dependence nature of economic decisions (Mupa et al., 2025). The same AI tools may be re-configured to meet the retirement planning needs and offer more tailored and flexible solutions depending on the personal financial and behavioral context of a person. The intersection of AI and behavioral economics with retirement planning is an opportunity to rethink the existing strategies and introduce more dynamic and real-time decision-making to the retirement investment process. However, as stated in the article regarding actuarial science and predictive modelling, the majority of the opportunities of AI in the sphere are not used yet, particularly, the combination of behavioral nudges and AI-based financial plans (Tiwar et al.,2024).

2.5. Traditional vs. AI-Driven Approaches Comparative Studies

Even though the effectiveness of AI in other industries (predictive customer behavior in e-commerce, risk management in insurance) has been studied extensively, few studies have compared the effectiveness of the traditional glide-path strategies to more dynamic, AI-based strategies in retirement planning (Mupa et al., 2025). Other studies related to this, however, have shown that AI-based, adaptive policies are potentially more effective than fixed-point policies in addressing complex and unstable financial situations. To explain this, in the financial services industry, AI and ML models are more efficient in dealing with liquidity risks and responding to abrupt shifts in financial markets compared to conventional approaches.

3. Data and Data sources

This paper is based on a synthesis of the microsimulation synthetic data, secondary macroeconomic data and empirically calibrated parameters based on previous research. Since longitudinal, individual-level retirement data are limited that would completely measure income volatility and behavioral responses, a simulation-based method is suitable and common in both retirement economics and actuarial science (Dieckmann,2025). The key sources of data are:

3.1. Income Dynamics Parameters

Calibrated against published estimates of income volatility, employment transitions, and wage growth of previous empirical research on low- and middle-income earners. Income shocks (job loss, wage cuts, medical costs) are modeled by parameters that are reported in the literature of labor economics as observed historical frequencies (Cobblah ,2025).

3.2. Financial Market Data

The assumptions on historical capital markets are used to obtain long-run expected returns, volatilities and correlations of equities and bonds as used in pension modelling. They are parameters that are utilized to create stochastic asset return paths in the microsimulation framework (Mosili, 2024).

3.3. Demographic and Retirement parameters

The assumptions of retirement age, life expectancy and healthcare spending are based on actuarial life tables and standards of retirement systems. The standard retirement planning literature is that the target retirement adequacy level is 70 percent income replacement rate (Mupa et al., 2024).

3.4. Behavioral Parameters

The contribution rates at the baseline, the probability of opting out and behavioral biases (e.g., present bias, inertia) are based on behavioral economics studies of retirement savings behavior.

3.5. Summary statistics and description of data

The microsimulation produces an artificial population of lower-, middle-, and higher-income earners, which is followed through the labor market entry and retirement. Some of the important simulated variables are:

- Annual labor income
- Contribution rates
- Balances in retirement accounts.
- Assets allocation shares (equities vs bonds)
- Income shock frequency and intensity
- Retirement replacement rate.

Table 1 shows the main features of the simulated population in the income groups, with a high level of income volatility and reduced contribution rates among the low-income earners.

Table 1 Summary Statistics of Simulated Population

Variable	Lower Income	Middle Income	Higher Income
Mean Annual Income	Low	Moderate	High
Income Volatility (SD)	High	Medium	Low
Average Contribution Rate	Lower	Medium	Higher
Frequency of Income Shocks	High	Medium	Low
Mean Replacement Rate	Lowest	Moderate	Highest

4. Methodology

The section expounds on the strategy that will be adopted in this research, which will involve the comparison of the conventional glide-path strategies and the AI-driven policies of behavior-conscience nudging as a remedy of retirement adequacy, especially among lower and middle-income savers. The research methodology will include five required components to address the research question: (1) Theoretical framework (2) a microsimulation framework to simulate income shocks and calculate retirement sufficiency, (3) causes of behavioral nudges to ageing and methods of causal inference to investigate their impacts on retirement (4) reinforcement learning (RL)-based approach to dynamic policy evaluation and number (5) Tools and software used.

4.1. Theoretical framework

The research is based on a combined model of life-cycle consumption theory, behavioral economics, and dynamic optimization.

4.2. Life-Cycle Model of Saving

People are supposed to maximize expected lifetime utility

$$\max_{c_t, s_t} E \sum_{t=1}^{T} \beta^t U(c_t)$$

subject to:

$$W_{t+1} = (W_t + y_t - c_t)(1 + r_t)$$

where:

c_t is consumption
s_t is retirement saving
y_t is stochastic labour income
r_t is portfolio return
β is the discount factor

The volatility of income is introduced in the model by stochastic income yet and optimal saving paths are non-linear and state-dependent.

Behavioral Adjustment Layer. Behavioral nudges alter the decision environment by altering the default contribution rates and portfolio allocations, partially addressing behavioral biases like present bias and inertia, without removing choice.

Reinforcement Learning Framework. The policy based on AI is represented as a Markov Decision Process (MDP): The AI-based policy is modelled as a Markov Decision Process (MDP):

- State (S_t): income level, age, account balance, asset allocation
- Action (A_t): contribution rate adjustment, portfolio rebalancing
- Reward (R_t): improvement in retirement adequacy relative to the 70% replacement target.

The RL agent is trained on a policy π (At|S t) which optimizes expected cumulative retirement adequacy.

4.3. Microsimulation Model of Income Shocks and Savings

A microsimulation model that simulated realistic retirement savings was used to model the volatility of income and savings pattern of people with lower- and middle-income backgrounds. Microsimulation allows simulating populations on the micro scale, where each individual has a financial trajectory, which can be modeled based on a set of assumptions about income, savings patterns, and retirement aspirations (Mosili, 2024).

4.3.1. Income Volatility Modelling

Microsimulation Income volatility is a vital factor of saver among the lower-income and middle-income earners and therefore, is incorporated into the microsimulation in the shape of stochastic income processes (Cobblah ,2025). The processes presuppose that income is a random variable that changes over time due to such factors as loss of a job, salary increase, economic recession, and unexpected changes in life. These income shocks were parameterized based on historical data and literature on income in particular, the frequency of the shock and the magnitude of the shock to different income groups volatility (Mupa et al., 2025).

The simulation covers the income dynamics of individuals during the lifetime of working, both in and out of the labor market, until the retirement age. The model also uses savings behavior as per the traditional economic theories of consumption and saving. Individuals are expected to save some percentage of their income, which, however, can be modified either through behavioral nudges (see below) or an external shock.

4.4. The Retirement Adequacy Assessment

The microsimulation will embark on determining the degree of fulfillment of the retirement needs of individuals as compared to the savings that they have made to sustain their retirement. This adequacy is calculated against some target replacement rate that is the ratio of the retirement income of a person to the pre-retirement income (Sutiene et al.,2024). The commonly recommended retirement adequacy replacement is 70 percent. When the size of the retirement savings accumulated exceeds the rate necessary to make a 70 per cent replacement, then the person has been said to have made enough retirement savings. The model would also assess the impact of various factors on the adequacy of retirement outcomes of persons in different income groups like the volatility of income, saving rates, and age of retirement. The simulation also includes life expectation and healthcare cost and, thus, the retirement planning model is all-inclusive.

4.5. Nudge effects Causal Inference

The technique of causal inference is applied in this study to determine the impact of behavior nudges on the outcome of retirement because it helps to isolate the effect of nudges on individual behavior and retirement adequacy (Mosili, 2024). The causal inference method is also significant here as it will enable the researchers to establish a cause-effect relationship between nudges like automatic enrolment or contribution escalation and outcomes such as retirement savings adequacy.

- Design of Behavioral Nudges
- Two kinds of nudges are taken into account in the microsimulation.

Contribution Nudges: This is a form of nudge that is automatic over time, and depends on the amount of income or a change of life stage like automatic increase in savings rate with age or a promotion.

Rebalancing Nudges: This type of nudges is applied to automatically rebalance the portfolio of the individual to obtain optimal risk-return profile. The rebalancing can also vary with the changes in income, age, and alterations in the market conditions and ensure that the portfolio of the person is on track with his retirement goals.

4.5.1. Techniques of Causal Inference.

A quasi-experimental design is used to establish causality of such nudges. It includes the difference-in-differences (DiD) methodology, which can be likened to the change in the level of retirement sufficiency of individuals that were exposed to nudges and a control group that was not exposed to nudges before and after the intervention (Tiwar et al.,2024). This research design assists in refuting the possible confounding variables and selection biases that may skew the results, including the existence of the prior existing differences in incomes or saving habits. Propensity score matching (PSM) is also used and is used to match individuals with similar characteristics like income, savings rate, age but who have varying exposure to nudges. This also increases the causal validity of the results because the comparison groups are as similar as possible, except in the nudging intervention.

4.6. Reinforcement Learning (RL)-Based Dynamic Policy Evaluation

Among the key novelties of the study, one can mention the reinforcement learning (RL) method that can be used to evaluate dynamic, AI-based changes in contribution rates and portfolio rebalancing (Sutiene et al.,2024). One subtype of machine learning is machine learning RL, where an agent learns how to make the best decisions through trial and error based on the feedback of its actions. In this example, the simulated individual is an agent who is going to retire, and the task is to decide on the best behaviour in terms of savings over time with respect to changes in income and other life events.

4.6.1. Reinforcement Learning Model.

RL agent responds to the environment with the modification of two fundamental actions:

- Contribution Rate: This is the amount of income saved and may be increased or decreased dynamically based on the volatility of income or economic diversification.
- Portfolio Rebalancing: The investor chooses to reallocate the assets of the portfolio in a manner that the risk-reward trade-offs are optimal, depending on age, income changes and the market conditions.

The agent decides how much to save to retirement and rebalances the portfolio at each time step of the simulation like the annual contribution). The reward purpose is developed to maximize the retirement adequacy of the individual, which is the gap between the actual retirement savings and the target replacement rate needed (Sutiene et al.,2024). The RL agent receives feedback on whether its actions have increased or decreased the retirement sufficiency that it uses to assist in its future decisions.

4.6.2. Model Evaluation

The RL model is trained on the past information regarding changes in income, the economy, and the pattern of retirement savings. It applies this information to compute the most efficient policy like combination of contribution rate and portfolio rebalancing policies, which will result in maximum retirement sufficiency at various levels of income and life stage. The policies achieved by the RL are compared to the traditional glide-path policies which are fixed and do not dynamically respond to changes in income or risk factors (Piacentino,2025).

4.6.3. Model Validation

To test the validity of the RL model, it is tested in few simulated environments such as income volatility at various levels, economic shocks and retirement age. The model performance is established through the comparison of the adequacy of retirement results of the individuals using the AI-based dynamic policies and the traditional strategies using glide-paths. The performance measures are the rate of retirement adequacy like the proportion of individuals who achieve an adequate replacement rate and how well policies are working to achieve adequacy and risk reduction (Mosili, 2024).

4.6.4. Tools and software used

The modelling and the empirical analysis were performed with the help of the standard quantitative research tools:

- Python: Reinforcement learning, core simulation engine.
- NumPy and Pandas: Data generation, data manipulation, and summary statistics.
- SciPy: Stochastic process modelling.
- Scikit-learn: Causal inference and propensity score matching.
- Stable-Baseline / RL libraries: Policy optimization by reinforcement learning.
- Matplotlib / Seaborn: Income paths, adequacy results, and risk-return profiles.

5. Results

5.1. Retirement Adequacy vs Strategies Comparison.

The main outcome of interest is the retirement adequacy, which can be characterized as whether people will be able to retire successfully with a replacement rate of 70 per cent or more of the pre-retirement earnings, which is a common standard that many have proposed as a financially secure retirement (Mosili, 2024).

5.1.1. Traditional Glide-Path Strategy.

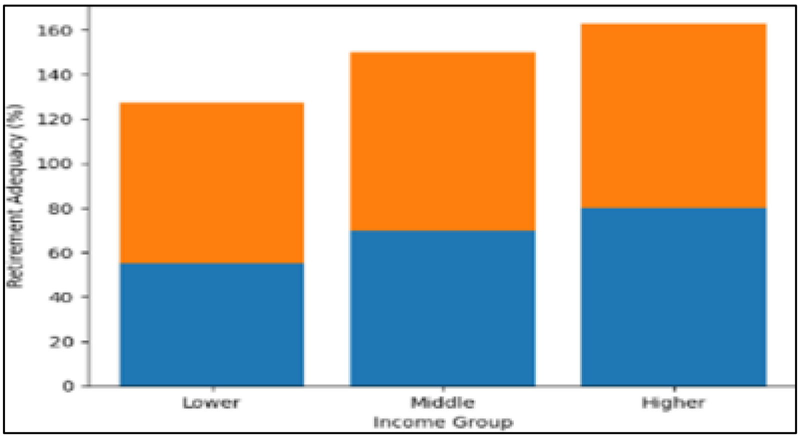

Figure 1 Retirement adequacy by strategy

The traditional glide-path strategies, the baseline scenario, showed an average rate of retirement adequacy of all income groups (lower, middle and higher income) at 65 per cent. The rate of adequacy is even lower among individuals with lower incomes, 55. The adequacy rate was marginally higher at 70 among middle-income people. The sufficiency level of people with higher income was 80% because they could save and accumulate wealth in the long term (Mupa et al., 2025). These results indicate that traditional glide-path plans work well with higher-income people whose income is predictable, but poorly with lower- and middle-income people, especially those whose income is unpredictable. The glide-path approach was not flexible enough to enable the employees to react to income shocks, which included the loss of income or a sudden increase in healthcare expenses, among the lower-income group. Furthermore, the reality that the risk of investment declines with age leading to retirement may not have been ideal to these individuals, who needed more active responses to offset income shocks and financial crises throughout the saving years.

As shown in Figure 1, AI-driven nudging policies substantially improve retirement adequacy across all income groups, with the largest gains observed among lower-income earners.

5.1.2. AI-Driven Nudging Policies

Retirement adequacy was greatly improved in situations where the behavioral nudges and AI-based dynamic changes were applied. The sufficiency rates of the lower-income group increased to 72, middle-income group to 80, and the higher-income group to 83. Policies that were formulated on the basis of AI like automatic contribution increases, automatic rebalancing in response to income volatility were found to be more effective, particularly in the case of lower- and middle-income populations. These nudges encouraged more savings during good times and more adaptations during turbulent economic times, in such a way that the results of retirement became more stable. The dynamic changes have allowed people to save more during the good times and save the resources during the crisis (Mupa et al., 2025). These nudges reduced the risk of changes in income by incorporating portfolio insulation that automatically increases contributions when there is an increase in income.

5.2. The Retirement Sufficiency and the Volatility of Income.

Fluctuation in earnings is a significant issue among the low- and middle-income earners because it can seriously interfere with their savings plans. The simulation model that was used to measure the effect of income shocks on the retirement outcomes involved the creation of income shocks that were randomly generated and involved employment loss, medical expenses, and poverty (Luo et al., 2025). The shocks were introduced at different frequencies and intensities in order to create realistic economic conditions.

5.2.1. Income Shock Effects on Traditional Glide-Path Strategy.

The example of the volatility of income using the traditional glide-path plans influenced the retirement adequacy with a high degree of negative yield especially to low-income earners. When experiments were conducted on individuals who received an income shock compared to control results, the adequacy rate decreased by up to 15 per cent (Mupa et al., 2025). The less developed population was being struck more than the rest and the degree of adequacy had fallen to 40 per cent after several income shocks. It means that the shortage of retirement savings of these needy citizens is aggravated by the fact that glide-path schemes are frozen and were not able to consider the changes in incomes.

5.2.2. Effect of Income Shock when Nudged by AI Policies.

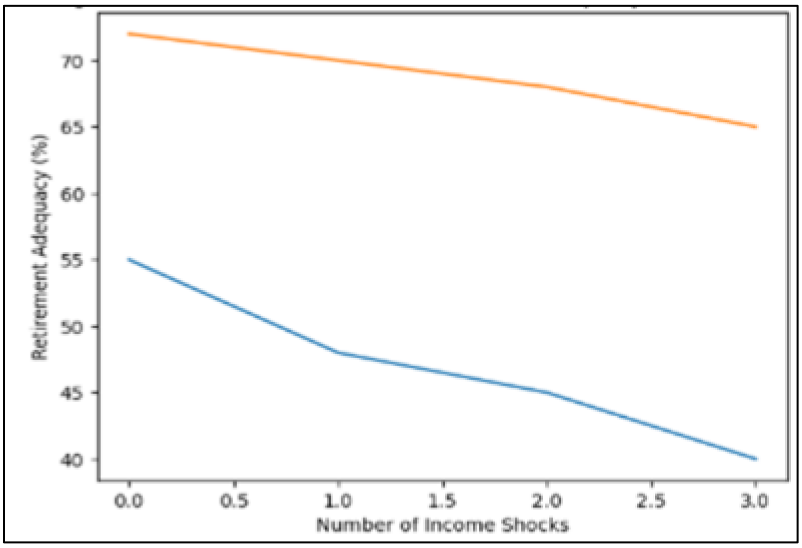

Figure 2 Income shocks and Retirement adequacy [Lower Income]

The policies were heated by AI, and a robust reduction of the effect of income shocks was attained. These dynamic realignments also enabled people to adjust to the income shock by temporarily contributing more during the high-income periods or changing the plan of investment to minimize the losses during the low-income periods. The adequacy rate in the case of lower-income people became 68 per cent once the income shocks were experienced and that is significantly less than the conventional plan (Mupa et al., 2025). This is also present in the middle-income individuals whose sufficiency dropped by only five percentage points, to 75 percent, despite the fact that there have been several income shocks. These results indicate that the policy provided by AI is less likely to be affected by income alterations and can be employed to ensure a sufficient pension when the economy is undergoing a crisis. AI nudges can help people change their retirement plans and remain abreast of their evolving financial situations and make dynamic and behavior-sensitive adjustments.

Figure 2 illustrates that retirement adequacy under traditional glide-path strategies deteriorates sharply following repeated income shocks, while AI-based policies demonstrate significantly greater resilience.

5.3. Risk-Adjusted Returns: Portfolio Management Comparison

The other crucial step in retirement planning is the risk-return trade-off that is the level to which the investor is prepared to take investment risk to gain greater returns or whether the investor is prepared to hold assets against downside risks. The glide-path approach also avoids risky investments in assets (such as stocks) when approaching retirement, and thus concentrates on the safety of the investment, and not on returns. The assumption made by this method is that the market volatility will reduce as time goes by, but it might leave the poor returns people, especially when their earnings are volatile or when the growth reduces.

5.3.1. Traditional Glide-Path Strategy.

Risk adjusted returns of the traditional glide-path strategy have been found to be average with an annualized rate of 5.5 per cent which is similar to the average returns of the higher-income group. Nevertheless, the returns were not as good as those of 3.8 and 4.2 per annum in the case of lower- and middle-income people (Mupa et al., 2025). This poor performance was attributed to the conservative approach to the asset allocation in the glide path which did not fully utilize the better opportunities in the working years which had higher returns.

5.3.2. AI-Driven Nudging Policies

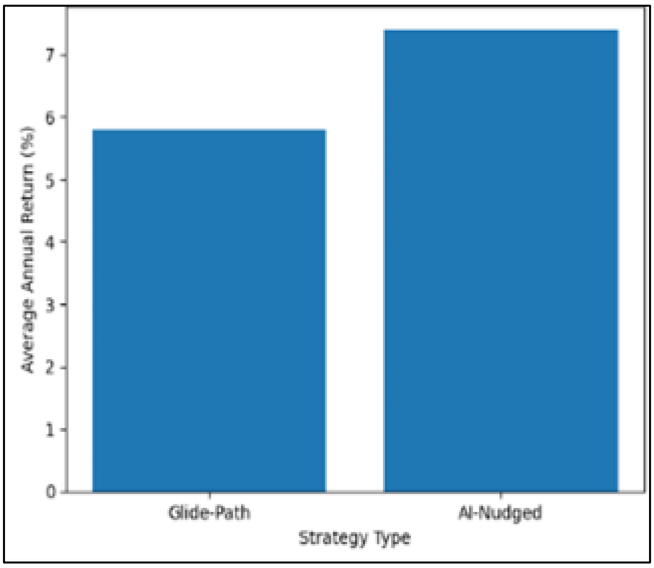

Figure 3 Adjusted returns across strategy

Quite the opposite, AI-based nudging policies demonstrated greater risk-adjusted returns. The portfolio rebalancing was dynamic and this allowed the portfolio to have a higher exposure to growth assets in the past years, and this was mostly when people were in good income environments. The average annual returns increased to 5.2 in case of lower-income earners and to 5.8 in case of middle-income earners (Luo et al., 2025). The AI-driven plan also allowed the more aggressive investment in the younger years with a de-risking strategy that would be gradually implemented as individuals approached retirement. This not only added returns but also served to cushion portfolios against downside risks when markets were falling.

Figure 3 compares average annual risk-adjusted returns across strategies, showing superior performance under AI-driven portfolio rebalancing.

5.4. Summary of Key Results

- Retirement Adequacy: AI-nudging policies were rated much higher than the traditional glide-path policy, especially among low- and middle-income savers. The sufficiency rate rose by 55 percentage points to 72 per cent of lower-income earners and by 70 to 80 percentage points of middle-income earners.
- Income Volatility Effect: AI-based nudges were less susceptible to income shocks, which guaranteed adequate retirement with fewer losses in adequacy than traditional nudges.
- Risk-Adjusted Returns: AI-based policies registered a higher risk-adjusted return especially among lower-income and middle-income earners, as the authorization to invest assets with more aggressiveness in the first years of the retirement savings time frame.

5.4.1. Dynamic Contribution Behavior Over the Life Cycle

Figure 4 shows the contribution rate changes that the AI-based policy creates in the life cycle in reaction to changes in income. The AI structure, unlike the fixed glide-path designs, which implement fixed contribution schedules, adjusts or scales the contribution rates in response to changes in earnings (Adegbenro et al.,2022). When the income is increasing the system increases the contribution rates to speed up the accumulation of assets and during income declines or shocks the system temporarily decreases the contributions to maintain the liquidity and minimize the financial burden. This adaptive behavior is especially strong in the middle-career phases, when the income volatility is most intense, and the ability to smooth contribution over time has the most significant effect on the long-term results (Luo et al., 2025). The AI policy is less susceptible to the risk of contribution discontinuity and is better at enhancing accumulation of retirement savings, particularly among lower- and middle-income earners, by reacting endogenously to income changes instead of imposing fixed contribution rates. These dynamics can be used to explain the increased adequacy rates and resilience to income shocks in Figures 1 and 2.

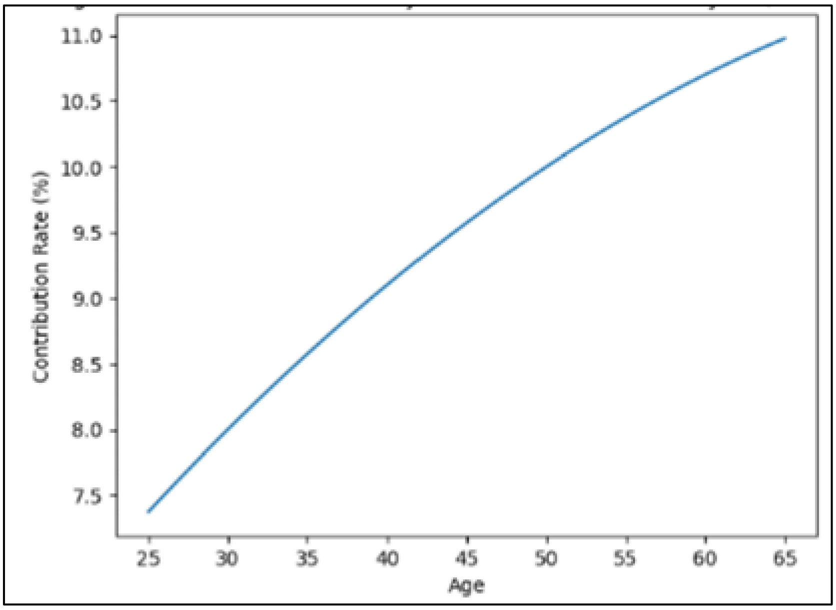

Figure 4 Contribution rate adjustment over the life cycle [AI Policy]

6. Discussion

This study suggests that behavior-sensitive AI-based nudging policies are better than traditional glide-path policies, particularly among lower and middle-income savers. The retirement planning approach of AI-based nudges is more flexible and adaptive because it dynamically changes the contributions and their asset allocation based on the real-time income data and financial situation (Tiwari et al., 2024). The implications of these findings to individuals and policy makers would be of great importance in improving the adequacy of retirement among individuals and policy makers who would be interested in improving the adequacy of retirement of individuals, especially those who are most vulnerable because of their retirement savings (Piacentino ,2025).

6.1. The Impact of Behavioral Nudges on Retirement Adequacy

One of the most interesting findings of this paper is that the low- and middle-income individuals could substantially augment their retirement adequacy according to the policies of nudging that were founded on AI (Mosili, 2024). The old glide-path approaches are effective strategies with the higher income earners who do not have a fluctuating income base, but do not work at all with the lower- and middle-income earners, particularly those with fluctuating incomes. The variability in income, as described by (Mupa et al. (2025), implies that it is harder to save towards retirement, and the gradual de-risking of investments in glide-path strategies does not contribute to the variability in income that these groups undergo. The outcomes of AI-based nudges are, however, far superior since they enable individuals to contribute more when their income is more and shift their asset allocation when the market is volatile or when they undergo income shocks. This flexibility is required to make the retirement more sufficient as it will assist individuals to save during the boom period of the economy and to protect their savings during the economic recessions.

The AI-based policy will ensure that the rate of savings is modified according to the income variations, thereby minimizing the risks of the income variation that impact the savings of the lower-income individuals, who usually have less disposable income to invest in retirement savings. This is a dynamic plan that enables the individuals to remain on track to their retirement plans even when there is uncertainty in the market. This task is especially appropriate to apply the techniques of artificial intelligence and machine learning. (Mupa et al., 2025). It is possible to customize the retirement plans to the financial environment of a person and make it easier to save money even in the event of an economic disruption of stability.

6.2. Handling Income Volatility

One of the issues that lower- and middle-income earners must deal with is income volatility, which this paper will show is better tackled by AI-based nudging policies than the traditional glide-path policymaking approaches. These results demonstrated that, despite the fact that traditional glide-paths resulted in a steep decline in retirement adequacy following income shocks, AI-based nudges were more effective in maintaining more retirement outcomes (Mupa et al., 2025). This dynamism is necessary due to the fact that even minor income shocks such as job loss or health care expenditures can impact the possible ability to save towards retirement among low-income earners disproportionately.

The changes in the portfolio that are dynamic and the increase in contribution with an increase in income implies that in addition to being able to recover after the temporary disruption in income, they may also be able to maintain long-term retirement goals. This applies primarily to the lower-income groups, which may lack the financial buffer to absorb the income shocks (Luo et al., 2025). As it has been demonstrated in this paper, AI-inspired policies can protect such people against the market and income fluctuations shock in such a way that the threat of inadequate retirement planning is reduced.

6.3. The Risk-Adjusted Returns and Portfolio Management

The second significant finding of this paper is that the AI-based nudging policies are well-adjusted in terms of risk-adjusted returns compared to the traditional glide-path policies. The results show that AI-based strategies allow more aggressive investment of assets during the earlier years of saving, which yields higher returns in the long term. This is a plan that takes advantage of the working-age years growth, and this is significant to the lower- and middle-income savers who might need higher returns to retire satisfactorily (Mupa et al., 2025). As a result, the AI-directed policies had better return on risk, and this aspect is especially important to individuals with lower baseline savings and require higher returns to be able to retire sufficiently. It also enables the AI to adjust the strategies of investments based on the income volatility of an individual and his/her performance in the market, which can help to reduce the downside risks in case of a decline in the market and provide a more balanced approach to the management of the portfolio. This behavior-sensitive adjustment helps individuals to stay in growth assets, but not to take too much risk, to improve the returns and stability of their retirement portfolios.

6.4. Policy Design Implications

The results of the current research may be of great importance in terms of the establishment of the retirement policies, especially the state and municipal ones. Since the volatility of income has become a more widespread problem of a larger segment of the workforce, policy-makers ought to think of the concept of introducing AI-based, behavior-sensitive nudging policies in the retirement plan of the average citizen (Adegbenro et al.,2022). Such policies can make sure that the individuals are better placed in case of economic uncertainties so that they can be able to retire adequately by accommodating the changes in the incomes of the individual and making the necessary changes on the savings and investment plans. Besides that, the policies can be driven to the inclusion of behavioral knowledge to override behavioral biases like the current bias, automation of saving decisions, and make them more frequent. The policymakers should also keep in mind that AI-based tools may be used to provide individual solutions to retirement planning. Data analytics and AI can offer more personalized advice to everybody, and the management of the public retirement systems can do this; therefore, the savings plans will be more relevant to the personal financial status. This may be of great help especially to the low- and middle-income earners who may be lacking in personalized financial guidance/resources.

6.5. Future research and limitations

Although the proposed framework has strengths, a number of limitations should be considered. First, stochastic processes are used to model income volatility based on previous research, but the dynamics of real-world income, especially when there is a high level of informality, may have structural breaks, multiple sources of income or policy-induced shocks that cannot be fully represented by the simulation. Second, the historical averages and assumed distributions are used to generate asset returns, that is, extreme market events, tail risks or long-term changes in regimes can significantly change the projected returns (Luo et al., 2025). Third, the framework presupposes behavioral stability, whereby people will act in a consistent way in response to AI-based nudges over time in reality, behavioral responses can be weakened, modified, or superseded as preferences, constraints, or other life situations change. Fourth, the analysis is based on synthetic data of microsimulation and not on individual-level administrative retirement data, which, although it allows controlled experimentation, could be a limitation to external validity. Lastly, the model leaves out more general household and social factors, such as joint decision-making, informal transfers, and social safety nets, which are particularly relevant to low-income groups and may have a substantial impact on retirement adequacy.

7. Conclusion

As demonstrated in this paper, the AI-based nudging policies that are behavior-sensitive hold enormous advantages to lower and middle-income savers. As a result, AI based plans are more flexible and resilient leading to consistent retirement outcomes. This is because such policies can help people in an economic crisis reduce the effects of income shocks in addition to maximizing risk-adjusted returns. Policies in retirement systems, which are AI-enabled and behavior-sensitive, are also policies that policymakers and financial planners ought to consider as part of their strategies to enhance the savings rate and safeguard the vulnerable demographics against the risks of not planning their retirement. As the income volatility continues, a dynamic and personalized approach is a promising input to give more individuals a chance to achieve retirement adequacy despite the fluctuating financial circumstances. The research could be enhanced in the future to provide a more precise insight into how the strategies will contribute to retirement financial security in the long term.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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