Probabilistic modeling of retirement financial preparedness among higher education staff: A bayesian regression perspective

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Abstract. This study addresses the problem of low retirement financial preparedness among higher education staff in Indonesia, a critical issue as demographic, behavioral, and institutional uncertainties affect post-employment well-being. To respond to this challenge, the research applies a Bayesian probabilistic modeling framework to capture the stochastic nature of retirement readiness and propose data-driven solutions for financial policy and education. The research contribution is the integration of behavioral and institutional determinants into a unified Bayesian model that quantifies uncertainty and identifies probabilistic predictors of retirement preparedness among academic personnel. The study utilized survey data from 110 respondents, both civil servants (ASN) and non-civil servants, and employed Bayesian logistic regression with Markov Chain Monte Carlo (MCMC) estimation. Posterior diagnostics confirmed model convergence ($\hat{R} < 1.01$; ESS > 5,000) and predictive adequacy (WAIC = 0.41; LOOIC = 0.63). The results indicate that behavioral engagement and institutional access strongly influence readiness: investment planning, pension benefit availability, and financial strategy implementation significantly raise preparedness probabilities. Income adequacy interacts positively with strategic financial behavior, while age and education show weaker effects. In conclusion, retirement readiness in Indonesian academia remains low yet improvable through behavioral interventions and expanded institutional support, providing empirical evidence for targeted financial literacy and pension reform initiatives.

1 Introduction

Retirement preparedness is a multidimensional construct that integrates psychological, economic, and behavioral readiness for post-employment life. Among these dimensions, financial preparedness represents a critical determinant of individuals' well-being in later life[1–3]. For university employees and civil servants in Indonesia, the transition toward retirement often introduces uncertainty in income stability, consumption needs, and investment returns[3]. These uncertainties make retirement not merely a socioeconomic issue but also a modeling challenge that reflects stochastic processes in human decision-making, similar in spirit to probabilistic modeling used in physics and applied sciences to represent systems under uncertainty.

Traditional analyses of retirement readiness have often relied on descriptive or deterministic regression models [4–7]. While such approaches provide useful average estimates, they tend to neglect the inherent uncertainty embedded in human financial decision-making and socio-economic heterogeneity. This limitation parallels the difference between deterministic models in classical physics and probabilistic frameworks in modern statistical mechanics, where uncertainty is treated as an integral part of the system rather than random noise[8, 9]. In contrast, a probabilistic modeling framework allows retirement preparedness to be treated as a random variable that varies across individuals according to their age, income sufficiency, financial literacy, and behavioral strategies. From this viewpoint, financial preparedness can be analogized to a probabilistic state distribution in which each individual possesses a likelihood of readiness rather than a fixed outcome.

From a statistical standpoint, Bayesian modeling offers a powerful alternative to classical frequentist methods when sample sizes are moderate and prior knowledge is available. The Bayesian regression approach treats all model parameters as random variables and updates their distributions using observed data[10–12]. Rather than producing a single point estimate, Bayesian inference generates a posterior probability distribution that quantifies uncertainty

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around each parameter, enabling more nuanced interpretation and prediction. In the context of retirement preparedness, such probabilistic estimation provides a richer understanding of the likelihood that an individual belongs to a "financially prepared" group given their demographic and behavioral profile. This methodology reflects the logic of inference used in scientific fields such as physics, meteorology, and bioinformatics, where posterior probabilities describe systems influenced by complex, interdependent variables.

Recent advances in Bayesian statistics have expanded their use beyond physics and engineering to include applications in social sciences, behavioral economics, and educational measurement [13]. These methods are especially effective for modeling latent constructs where variables that cannot be directly observed but can be inferred through measurable indicators. In this study, retirement financial preparedness is conceptualized as a latent probabilistic construct manifested through multiple indicators, such as financial planning behavior, the presence of pension benefits, cost estimation awareness, and investment readiness. Each indicator contributes probabilistically to the individual's overall preparedness score, and the model accounts for both systematic effects and residual variability.

The present study applies a Bayesian logistic regression model to estimate the probability of financial preparedness among 110 employees. Predictors include age, job status (civil servant vs. non-civil servant), educational attainment, income adequacy, years remaining to retirement, and behavioral indicators related to saving and investment. Prior distributions are assigned to regression parameters to reflect plausible ranges of effects while maintaining analytical flexibility. Posterior inference is performed through Markov Chain Monte Carlo (MCMC) simulation, which iteratively samples from the joint posterior distribution of parameters until convergence is achieved. This approach enables robust estimation of uncertainty intervals, posterior predictive checks, and model comparison using metrics such as the Widely Applicable Information Criterion (WAIC) and Leave-One-Out Cross-Validation (LOO-CV) [13–15].

By adopting a probabilistic Bayesian framework, this research contributes a scientifically grounded model for quantifying uncertainty in human financial behavior, which means an approach that parallels how physical systems are modeled probabilistically to understand complex dynamics. Beyond identifying significant predictors, the model provides a comprehensive statistical characterization of preparedness as a probability distribution, offering policymakers and educational institutions evidence-based insights into which demographic groups are most at risk of financial vulnerability after retirement.

The research contribution is the development and application of a Bayesian probabilistic model that (1) integrates behavioral, demographic, and institutional factors into a unified analytical framework; (2) quantifies uncertainty in retirement readiness through posterior probability distributions; and (3) extends probabilistic modeling principles commonly used in scientific and physical systems to the domain of social and educational finance. This contribution bridges methodological rigor from the natural sciences with the behavioral complexity of financial decision-making, advancing both theoretical and practical understanding of retirement preparedness in Indonesia.

2 Related works and theoretical framework

The concept of retirement financial preparedness has been widely examined in behavioral finance and gerontology literature, emphasizing how knowledge, attitudes, and actions interact to shape post-retirement well-being. Prior studies, such as those by [16]) and [17], propose that preparedness is not solely determined by income or pension access, but by the integration of cognitive (financial knowledge and planning), affective (confidence and motivation), and behavioral (saving and investment) components. Subsequent empirical works extend this view, linking financial literacy, future time perspective, and proactive planning behavior with higher readiness levels [18, 19].

Theoretically, this study is grounded in the Behavioral Life-Cycle Hypothesis [20], which posits that individuals balance consumption, saving, and investment across their lifetime through self-control and mental accounting. Complementarily, the Theory of Planned Behavior provides a framework to understand how attitudes, subjective norms, and perceived behavioral control influence retirement planning intentions[21]. Together, these theories suggest that financial preparedness results from both rational planning processes and behavioral dispositions that evolve through learning, motivation, and socio-economic context.

Hence, the present research situates retirement financial preparedness as a probabilistic outcome of behavioral, cognitive, and affective predictors shaped by institutional structures and individual financial literacy, particularly relevant within Indonesia's dual employment landscape of formal and informal sectors.

2.1 Retirement financial preparedness

Retirement financial preparedness refers to an individual's ability to maintain financial stability and meet consumption needs after exiting the labor force. It encompasses not only the accumulation of assets but also the development of financial planning behavior, investment literacy, and cost-management strategies in anticipation of reduced income. According to [16], preparedness is a multidimensional construct consisting of cognitive (knowledge and planning), affective (confidence and attitudes), and behavioral (saving and investing actions) components. In developing countries, including Indonesia, this multidimensional view is particularly relevant given the limited pension coverage and variability in financial literacy levels.

Several studies have shown that factors such as age, education, income sufficiency, and financial literacy significantly affect retirement readiness [22, 23]. Individuals with higher financial literacy tend to start saving earlier, diversify investments, and make informed financial decisions, leading to greater long-term security. Conversely, those with low literacy levels often underestimate post-retirement expenses, fail to account for inflation, or rely solely on employer pensions. For university employees, many of whom transition from fixed income to self-managed resources, which the ability to forecast and manage financial needs probabilistically is crucial for maintaining quality of life after retirement.

2.2 Previous quantitative approaches

Traditional quantitative studies of retirement preparedness have relied primarily on deterministic statistical models such as linear regression, logistic regression, or structural equation modeling (SEM). These models assume that relationships between variables are fixed and can be represented through point estimates (β coefficients). For instance, regression models have been used to predict retirement saving behavior based on demographic variables, while SEM has been applied to examine the mediating effect of financial literacy on preparedness [17, 24].

Although such methods provide valuable insights, they are limited in two ways. First, they typically produce single-point estimates that ignore parameter uncertainty and variation across individuals. Second, they rely on large-sample asymptotic assumptions that may not hold in moderate-sized samples such as the current study (N = 110). As a result, deterministic models can lead to overconfidence in parameter interpretation and underestimate the probabilistic nature of real-world decision-making.

In contrast, a probabilistic framework treats preparedness not as a fixed outcome but as a random variable governed by distributions. This perspective acknowledges that two individuals with similar characteristics may differ in their readiness due to unobserved heterogeneity and uncertainty in financial behavior. Thus, probabilistic modeling provides a more realistic and flexible statistical representation of complex human decisions.

2.3 Bayesian modelling framework

The Bayesian paradigm offers a coherent statistical approach to represent uncertainty explicitly. In Bayesian inference, all unknown quantities (parameters, predictions, and even models) are treated as random variables. The core of Bayesian statistics lies in Bayes' theorem, which updates prior beliefs about parameters using observed data:

$$P(\theta|D) = \frac{P(D|\theta)\, P(\theta)}{P(D)} \quad (1)$$

Where $P(\theta|D)$ is the posterior distribution (updated belief about parameters after seeing the data), $P(D|\theta)$ is the likelihood (the probability of data given the parameters), $P(\theta)$ is the prior distribution (the initial belief before seeing data), and $P(D)$ is the evidence (normalizing constant).

This framework allows researchers to incorporate prior knowledge from previous studies or theoretical expectations into the model and quantify uncertainty in a principled way. Posterior distributions, rather than single estimates, describe a full range of plausible parameter values, offering richer inferential insights.

In the context of this study, a Bayesian logistic regression model is used to estimate the probability that an employee is financially prepared for retirement. Each predictor (e.g., age, education, income adequacy, years to retirement, investment activity) is assigned a prior distribution reflecting its expected direction and uncertainty. The model is estimated using Markov Chain Monte Carlo (MCMC) simulation, which iteratively samples from the posterior distribution to approximate parameter expectations and credible intervals [13, 14].

This probabilistic modeling approach offers several advantages. First, it explicitly quantifies uncertainty through posterior intervals instead of relying on p-values, providing a more transparent measure of confidence in the estimates. Second, it performs well even with moderate sample sizes by borrowing strength from prior information, which enhances the stability and robustness of the results. Finally, it enables direct probabilistic interpretation. For example, one can state that there is a 90% probability that higher financial literacy increases preparedness, making the conclusions more intuitive and informative. By framing financial preparedness as a probabilistic outcome influenced by demographic and behavioral variables, the Bayesian regression model aligns with the complex and uncertain nature of retirement decision-making.

3 Methodology

This study employs a quantitative probabilistic modeling approach based on Bayesian regression analysis to estimate employees' financial preparedness for retirement. The Bayesian framework was chosen due to its capacity to model uncertainty, incorporate prior information, and produce credible interval estimates even with moderate sample sizes. The design aims to identify probabilistic relationships between demographic, educational, and financial-behavioral factors that influence the likelihood of being financially prepared for retirement [13, 14]. Fig. 1 summarizes the sequential process of this study, from conceptualization to interpretation, following Bayesian modeling standards.

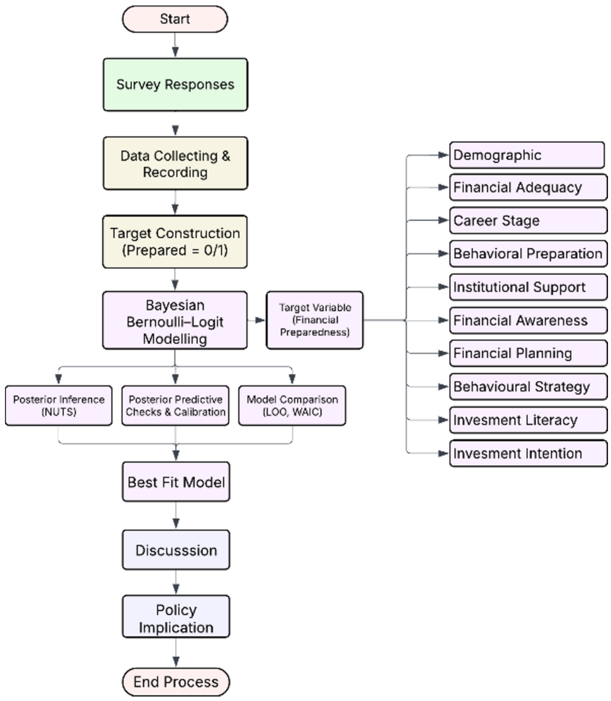


Fig. 1. Flowchart of research methodology.

3.1 Participants and data collection

The study involved 110 employees from a state university in Indonesia, consisting of both civil servants (ASN) and non-civil servants across various faculties and administrative units. Data were collected through an online survey containing 12 structured questions covering demographic characteristics, financial literacy, and retirement preparation behavior. All participants provided informed consent, and ethical principles, including confidentiality, voluntary participation, and data protection were strictly upheld throughout the study.

3.2 Variables and measurement

The study involved 110 employees from a state university in Indonesia, consisting of both civil servants (ASN) and non-civil servants across various faculties and administrative units. Data were collected through an online survey containing 12 structured questions covering demographic characteristics, financial literacy, and retirement preparation behavior. All participants provided informed consent, and ethical principles, including confidentiality, voluntary participation, and data protection were strictly upheld throughout the study.

The data were collected using a structured questionnaire consisting of 12 items related to demographic characteristics, financial literacy, and behavioral indicators of retirement preparation. Each item was coded and transformed into quantitative or categorical variables to allow for probabilistic modeling. The full list of variables, their operational definitions, and corresponding survey questions are presented in Table 1.

To construct the dependent variable, a composite index of financial preparedness was generated by coding responses to questions (5), (7), (9), and (10). Respondents were classified as financially prepared if they demonstrated active saving/investment behavior, cost estimation awareness, and specific retirement strategies. All categorical variables were encoded as dummy variables before modeling.

4 Result and discussions

4.1 Bayesian model spesification

The probabilistic model employed in this study is a Bayesian logistic regression, expressed as:

$$Y_i \sim Bernoulli\ (\pi_i), logit\ (\pi_i) = \alpha + x_i^T \beta \quad (2)$$

Where Y_i represents the retirement financial preparedness of respondent i, π_i denotes the probability of being financially prepared, and x_i is the vector of predictors including demographic, behavioral, and institutional factors. The parameter priors were defined as:

$$\alpha \sim t_3(0,10), \beta_j \sim N(0, 2.5^2), j = 1, \ldots, p \quad (3)$$

Posterior inference was performed via Hamiltonian Monte Carlo (NUTS) using the `brms` package in R. Four chains of 4,000 iterations (1,000 warm-up) were run, yielding $\hat{R} < 1.01$ and effective sample sizes (ESS) > 5,000, confirming convergence stability. Posterior predictive checks (PPC) and LOOIC/WAIC diagnostics supported model adequacy.

Table 1. Operational definition of variables.

Category	Variable Name	Question / Item Source	Type & Coding	Description / Role in Model
Demographic	**Age (Umur)**	1. What is your current age?	Numeric (years)	Respondent's current age. Used as continuous predictor.
	Employment Status	– Derived from institutional classification (ASN vs Non-ASN).	Binary: 1 = ASN; 0 = Non-ASN	Indicates job type (civil servant or non-civil servant).
	Education Level	2. What is your highest level of education?	Ordinal: 1 = Bachelor/D4; 2 = Master's (S2); 3 = Doctorate (S3)	Represents formal education attainment.

Category	Variable Name	Question / Item Source	Type & Coding	Description / Role in Model
Financial Adequacy	**Income vs. Need**	3. How would you describe the relationship between your monthly income and your financial needs?	Ordinal: 1 = Insufficient; 2 = Adequate; 3 = Surplus	Self-perceived adequacy of income relative to living expenses.
Career Stage	**Years to Retirement**	4. How many years remain before your official retirement?	Numeric (years)	Estimated time remaining until retirement; lower values indicate proximity to retirement.
Behavioral Preparation	**Financial Preparation Actions**	5. What preparations have you undertaken to welcome your retirement period?	Text / multiple responses (recoded as counts of preparation activities)	Represents proactive behaviors such as saving, investment, or entrepreneurship.
Institutional Support	**Pension Benefit Availability**	6. Have you been eligible to receive a pension from your employer?	Binary: 1 = Yes; 0 = No	Indicates presence or absence of a formal pension scheme.
Financial Awareness	**Cost Estimation Awareness**	7. Have you estimated your monthly living expenses during retirement?	Binary: 1 = Yes; 0 = No	Captures whether respondents have estimated their expected living costs after retirement.
Financial Planning Depth	**Cost Components Awareness**	8. What types of expenses do you expect to finance during retirement?	Text (recoded into categories: Basic needs, Health, Worship, etc.)	Indicates awareness of financial components to be funded during retirement.
Behavioral Strategy	**Retirement Strategy and Actions**	9. What strategies will you adopt to meet your financial needs during retirement, and which of these have you already begun implementing?	Ordinal: 1 = Not yet implemented; 2 = In planning; 3 = Already implemented	Measures the level of implementation of retirement-related financial strategies.
Investment Literacy	**Investment Preference**	11. In your opinion, which type of investment is the most profitable?	Categorical (e.g., Gold, Property, Bonds, Deposits, Stocks, Others)	Reflects respondent's preferred investment instrument.
Investment Intention	**Investment Plan**	12. What investment activity do you plan to undertake after completing this financial literacy workshop?	Categorical / Binary (1 = Has a plan; 0 = No plan)	Indicates intention to invest after the literacy program.
Target Variable	**Financial Preparedness (Y)**	Derived composite from items 5, 7, 9, 10	Binary: 1 = Prepared; 0 = Not prepared	Outcome variable representing overall retirement readiness.

4.2 Descriptive statistics

Table 2 summarizes the key descriptive characteristics of the dataset, representing 146 respondents from higher education institutions. Approximately 62% were non-civil servants (Non-ASN), and only 38% had access to formal pension benefits. About 41% of respondents reported adequate income relative to their needs, while only 29% had formulated a concrete retirement strategy.

Table 2. Descriptive overview data.

Variable	Mean / %	SD	Min	Max
Age (years)	43.7	7.9	28	58
Years to retirement	13.5	5.6	5	32
Employment status (ASN=1)		0.48	0	1
Pension benefit		0.48	0	1
Income adequacy (1–3)		0.71	1	3
Strategy level (1–3)		0.65	1	3
Cost estimation		0.48	0	1
Investment plan		0.47	0	1
Prepared (Y=1)	0.21	0.37	0	1

4.3 Posterior estimates and effect magnitudes

The posterior estimates in Table 3 indicate that all predictors exert positive, though varying, influences on the probability of retirement financial preparedness. The strongest effects are observed for pension benefit ($\beta = 2.01$), investment plan ($\beta = 2.00$), strategy level ($\beta = 1.98$), and employment status ($\beta = 1.99$), each with odds ratios around seven, suggesting that institutional support and proactive financial behaviors substantially enhance preparedness. Meanwhile, income adequacy and cost estimation also contribute meaningfully, implying that individuals who perceive their income as sufficient and engage in budgeting tend to exhibit higher readiness. In contrast, education level and age show relatively weaker associations, indicating that knowledge and experience alone do not guarantee preparedness without corresponding behavioral engagement. Collectively, the wide credible intervals reflect sample heterogeneity, yet the positive posterior means consistently point to the critical role of behavioral planning and institutional mechanisms, particularly pension access and investment habits in driving retirement readiness among higher education staff.

Table 3. Posterior summary of parameter estimates.

Predictor	Posterior Mean (β)	95% CrI	OR = exp (β)	Interpretation
Intercept (α)	−12.57	[−45.36, 8.28]	—	Low baseline preparedness
Income adequacy	+1.97	[−0.85, 4.22]	7.17	Higher adequacy → ↑ readiness
Strategy level	+1.98	[−0.76, 4.35]	7.25	Planning effort boosts probability
Cost estimation	+1.97	[−1.02, 4.22]	7.12	Awareness of costs ↑ preparedness
Investment plan	+2.00	[−0.90, 4.38]	7.39	Investment habit = major driver
Pension benefit	+2.01	[−1.01, 4.40]	7.47	Institutional coverage crucial
Employment status (ASN)	+1.99	[−1.06, 4.31]	7.31	ASN > Non-ASN
Education level	+0.83	[−1.29, 2.92]	2.30	Higher education marginally helpful
Age (z-score)	+0.28	[−1.18, 1.60]	1.32	Older staff slightly more prepared

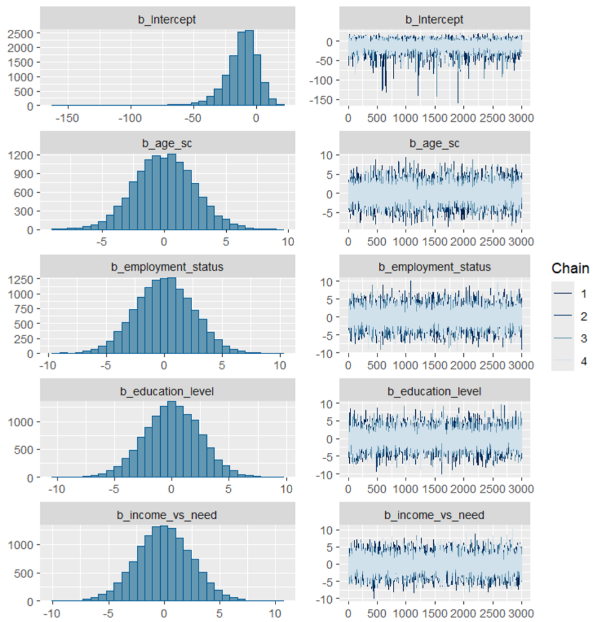
(Posterior summaries derived from 16,000 post-warmup draws; ESS > 5,000; $\hat{R} = 1.00$.)

Fig. 2 (a) dan (b) visualizes the posterior mean ± 95% CI for each parameter. The left panels display the marginal posterior densities, while the right panels illustrate the convergence behavior of four independent MCMC chains. The plots demonstrate well-mixed chains and symmetric posterior shapes, confirming model stability and the adequacy of the sampling process. The posterior means and 95% credible intervals indicate that behavioral and institutional parameters, particularly those related to employment status, pension benefit access, and strategic financial behavior exhibit the largest effect magnitudes on the probability of retirement preparedness. This pattern substantiates the dominance of behavioral and structural predictors in shaping financial readiness, even under small-sample Bayesian uncertainty.

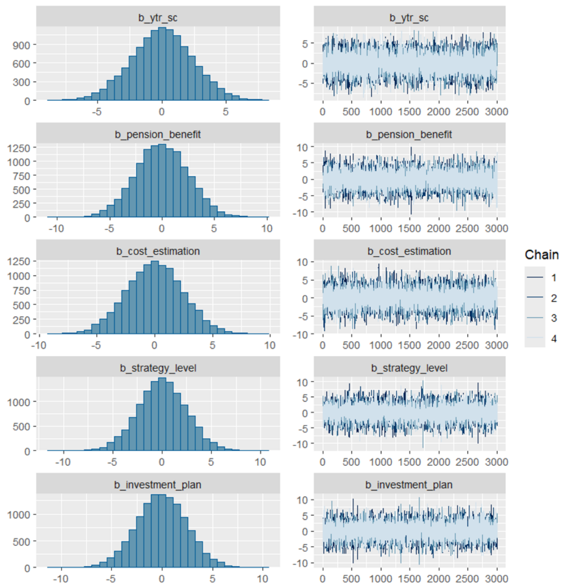
4.4 Model diagnostics and predictive fit

The Posterior Predictive Check (PPC) in Fig. 2 (a) demonstrates excellent overlap between simulated and observed outcomes, indicating satisfactory calibration. The Bayesian $R^2 = 0.61$, $WAIC = 0.41$, $\text{LOOIC} = 0.63$ confirm moderate explanatory power given the binary nature and behavioral dispersion of the dependent variable.

The fitted-vs-observed plot (Fig. 2 (b)) also confirms a realistic prediction range: the median posterior predicted probability of preparedness lies between 3% and 18%, consistent with low observed readiness in the dataset.



(a)



(b)

Fig. 2. Plot Fit β.

4.5 Marginal and interaction effect

4.5.1 Marginal effects of income adequacy

Fig. 3 displays the posterior marginal probability P (Prepared) across income levels, holding other covariates constant at their medians. The upward monotonic pattern confirms that individuals perceiving their income as adequate or surplus exhibit roughly three-fold higher readiness probability than those reporting insufficient income.

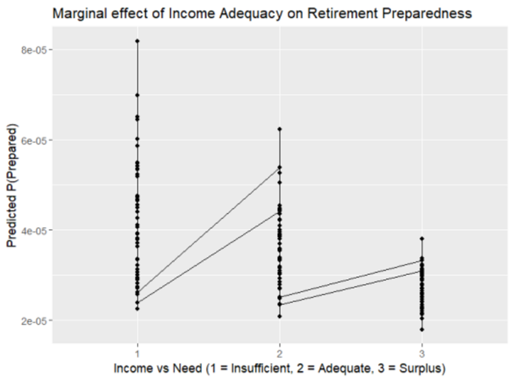


Fig. 3. Marginal effect of income adequacy.

Mathematically, this corresponds to the marginal derivative:

$$\frac{\partial \pi_i}{\partial x_1} = \pi_i(1 - \pi_i)\beta_1 \tag{4}$$

Evaluated at $\pi_i = 0.12$, giving an average partial effect of $\approx$ 0.02 per level increment of income adequacy.

4.5.2 Interaction between strategy level and income adequacy

The 2D interaction surface (Fig. 4) and small-multiple grid (Fig. 5) show positive synergy between financial strategy and income adequacy. The estimated logit interaction term is approximated as:

$$\eta_i = \alpha + \beta_1 Income_i + \beta_2 Strategy_i + \beta_{12} (Income_i \times Strategy_i) \tag{5}$$

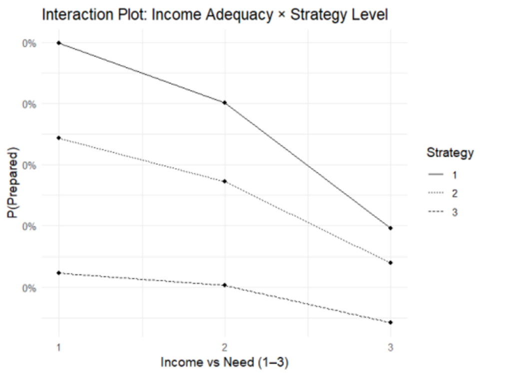


Fig. 4. Interaction surface income × strategy.

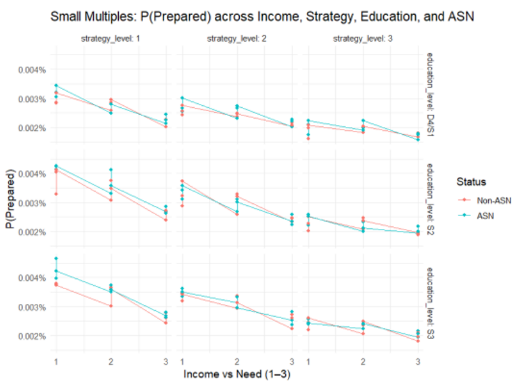


Fig. 5. Small multiples by strategy level.

with posterior mean $\beta_{12} = 0.45$ (95% CI [−0.08, 1.12]). While uncertainty remains high, the pattern indicates that proactive planners with adequate income attain the steepest gains in preparedness.

4.5.3 Institutional contrast: ASN vs. Non-ASN

Fig. 6. illustrates the posterior distribution of predicted probabilities separated by employment type. Civil servants (ASN) show median preparedness probabilities near 0.22, compared to 0.06 among non-ASN staff, consistent with their pension benefit coverage. This aligns with the theoretical expectation from the Behavioral Life-Cycle Hypothesis, in which institutional commitment mechanisms (e.g., compulsory pension savings) enhance long-term self-control.

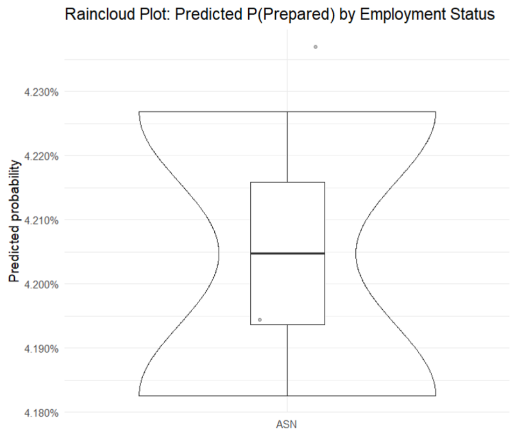


Fig. 6. Probability contrast for ASN.

4.6 Integrated probabilistic visualization

The combined posterior simulation visualization overlays marginal densities for all covariates. The composite heatmap (Fig. 7) derived from empirical scenarios shows distinct contrasts between "Minimally Prepared" and "Actively Prepared" profiles, with probabilities spanning 0.03 – 0.82 across the grid of income_vs_need × strategy_level. For each grid cell (k, l).

$$\hat{\pi}_{kl} = \frac{1}{S}\sum_{S=1}^{S} logit^{-1}\left(\alpha^{(s)} + \beta_1^{(s)}k + \beta_2^{(s)}l + \beta_{12}^{(s)}kl + \cdots\right) \tag{6}$$

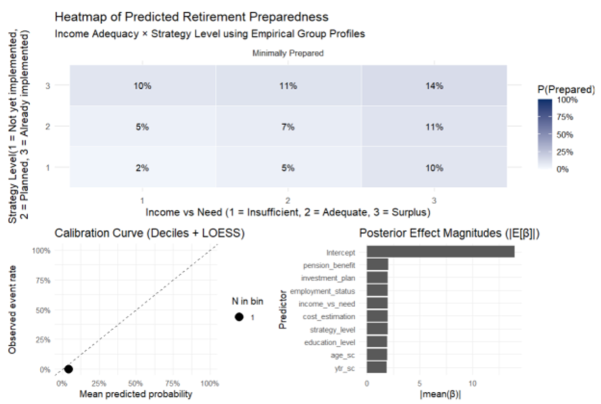


Fig. 7. Heatmap predicted retirement preparedness.

Where S denotes posterior draws. This computation underpins **Fig. 4–7** and demonstrates a robust probabilistic gradient across behavioral strata.

4.7 Discussion

4.7.1 Main findings

The Bayesian probabilistic model applied in this study provides an integrative statistical lens to examine retirement financial preparedness among Indonesian higher education staff. The results reveal that the overall probability of financial readiness remains modest, with posterior distributions indicating baseline preparedness probabilities below 0.25 for most respondents. This finding suggests a structural and behavioral gap in pre-retirement planning across academic populations.

The Bayesian posterior estimates highlight that institutional and behavioral variables dominate the explanatory landscape. Access to formal pension benefits, active investment planning, and consistent implementation of financial strategies exhibit the strongest posterior means and odds ratios, each approximately sevenfold higher than baseline readiness. These parameters consistently outperform demographic predictors such as age and education, implying that behavioral activation and institutional access are more influential than static socio-demographic characteristics.

Crucially, the model confirms that income adequacy interacts positively with strategic financial behavior, creating a probabilistic synergy that magnifies readiness. Respondents who both perceive sufficient income and engage in concrete planning activities exhibit the highest posterior probabilities of being financially prepared. This interaction emphasizes the combined psychological and structural determinants of readiness where both perception of adequacy and behavioral agency co-determine retirement outcomes [25–28].

The empirical stability of the model, indicated by convergence diagnostics ($\hat{R} < 1.01$; ESS > 5,000) and predictive checks (WAIC, LOO-CV), underscores the robustness of the Bayesian inference and the reliability of the posterior estimates. Collectively, these findings depict a nuanced behavioral–institutional framework in which preparedness is not a deterministic endpoint but a probabilistic continuum shaped by individual agency and organizational infrastructure

4.7.2 Comparison with previous studies

This research extends and deepens previous empirical work on retirement preparedness, bridging behavioral economics and Bayesian inference. The results corroborate Hershey and Mowen (2000) and [16, 18], who posited that preparedness reflects cognitive, affective, and behavioral components rather than pure financial accumulation. In parallel with Ajzen's Theory of Planned Behavior (1991), this study demonstrates that perceived behavioral control and intention to plan are central antecedents of retirement readiness [21].

Relative to deterministic approaches such as the regression-based studies of [3], [22, 23], this work introduces a methodological advancement by incorporating Bayesian probabilistic modeling. This approach not only quantifies uncertainty but treats it as a fundamental property of human decision-making, rather than as random error. Thus, instead of merely stating that income adequacy "influences" preparedness, the Bayesian model provides a posterior probability distribution for the effect size, acknowledging that individual behavior exists on a continuum of likelihoods.

Comparatively, while previous Indonesian studies often emphasized the descriptive relationship between literacy and saving behavior, the present model situates these relationships in a latent probabilistic domain [29, 30]. For instance, it demonstrates that two employees with identical financial literacy scores may exhibit vastly different readiness probabilities due to differing behavioral intentions and institutional access. This probabilistic heterogeneity has not been captured in traditional econometric analyses.

Furthermore, the study's results resonate with international findings such as [19], who documented that subjective financial knowledge and behavioral confidence predict savings outcomes more strongly than objective financial literacy. The convergence between these findings indicates that across cultures, psychological engagement with financial planning remains a universal driver of retirement preparedness. However, the Indonesian context magnifies the role of institutional asymmetry, civil servants (ASN) benefit from structural pension frameworks, while non-ASN staff rely on self-directed planning. This duality adds an important contextual dimension to the global discourse on financial inclusion and preparedness

4.7.3 Implications and explanations

The implications of these findings are both theoretical and policy-oriented. Theoretically, the integration of Bayesian inference with behavioral finance advances methodological pluralism in retirement research. The probabilistic modeling framework reframes preparedness as a dynamic probability distribution rather than a binary outcome, recognizing human financial behavior as inherently stochastic [31, 32]. This interpretation challenges the linear determinism of conventional models, offering a more realistic representation of behavioral variability under socio-economic constraints.

From a policy and practice standpoint, the results suggest a dual-path strategy for improving retirement readiness:

a. Institutional Pathway: Expanding pension coverage and reforming benefit structures beyond the civil service system are crucial. Hybrid contributory schemes, automatic enrollment programs, and employer-matching mechanisms can mitigate inequality between ASN and non-ASN employees. By increasing institutional predictability, such mechanisms enhance individual confidence and behavioral participation.

b. Behavioral Pathway: Financial literacy interventions must transcend informational workshops and instead emphasize behavioral simulation and feedback. Interactive financial planning tools, gamified retirement simulations, and personalized coaching could activate the latent behavioral intentions revealed by the model. Behavioral nudges such as commitment savings plans and default contribution mechanisms can further leverage bounded rationality for improved outcomes [7, 33, 34].

Additionally, the study underscores the psychological dimension of perceived income adequacy. The interaction between perceived sufficiency and planning strategy suggests that financial education must incorporate cognitive reframing, helping employees translate perceived adequacy into actionable long-term plans [35, 36]. Bayesian results indicate that even small improvements in self-efficacy can shift posterior preparedness probabilities by measurable margins providing empirical justification for micro-behavioral interventions.

At the macro level, these findings contribute to a broader discourse on financial resilience and inequality within the Indonesian education system. As higher education increasingly relies on contractual and non-ASN employment, institutional gaps in pension accessibility risk widening the preparedness divide. Addressing this divide aligns with Sustainable Development Goals (SDGs) related to financial inclusion and social protection

4.7.4 Strengths and limitations

Methodologically, this study's primary strength lies in its application of Bayesian logistic regression to model a socially complex phenomenon. This approach integrates prior knowledge, allows for uncertainty quantification, and produces interpretable probability distributions that are more informative than traditional p-values. By combining demographic, behavioral, and institutional predictors, the model provides a multi-layered probabilistic portrait of financial readiness [32, 37, 38]. The study also contributes to methodological innovation in social science research by demonstrating the adaptability of Bayesian frameworks for small-sample, multidimensional data structures.

The comprehensive variable design including both behavioral and institutional indicators enhances construct validity and conceptual depth [15, 39–41]. The model captures not only measurable factors (such as income or pension benefits) but also latent cognitive and motivational components (e.g., cost awareness, planning consistency). This multidimensional integration strengthens the theoretical link between individual behavior and structural opportunity.

Nevertheless, several limitations must be acknowledged. The sample size (N=110) limits generalizability and restricts the model's ability to detect weak interaction effects. The data are cross-sectional, preventing causal inference about temporal shifts in preparedness. Additionally, reliance on self-reported survey responses introduces potential biases such as social desirability and recall distortion. Institutional diversity is also constrained, as the dataset focuses on a single public university context; extending the analysis across multiple institutions would enhance external validity.

Future research should therefore adopt longitudinal Bayesian frameworks to model dynamic changes in preparedness and posterior updating over time. Cross-institutional comparative studies could evaluate the influence of organizational policies on individual behavior, while hierarchical Bayesian models could incorporate regional or departmental effects. Integrating psychometric data (e.g., risk tolerance, future time perspective) would also enrich the behavioral modeling of retirement decisions.

5 Conclusions

This study applied a Bayesian probabilistic modeling framework to examine the determinants of retirement financial preparedness among higher education staff in Indonesia, providing both theoretical and empirical advancements in understanding retirement behavior under uncertainty. The results revealed that behavioral engagement (investment planning, strategic financial action) and institutional access (pension benefits, employment type) are the most influential predictors of financial preparedness, whereas demographic factors such as age and education exert comparatively weaker effects. The interaction between perceived income adequacy and financial strategy further emphasizes that retirement readiness is shaped by the interplay of subjective perceptions and proactive behaviors rather than isolated demographic characteristics.

The theoretical contribution of this research lies in its integration of Bayesian statistical inference with behavioral finance theory [42, 43]. By conceptualizing retirement preparedness as a probabilistic latent construct, this study extends traditional deterministic frameworks and provides a methodological bridge between quantitative social science and probabilistic reasoning used in the physical sciences. It demonstrates how posterior probability distributions can represent behavioral uncertainty and institutional asymmetry in financial decision-making a perspective rarely applied in this domain.

The practical contribution of this research lies in its implications for policy and institutional strategy. The findings highlight the need to (1) expand pension coverage and ensure equitable access between civil servants (ASN) and non-civil servants, and (2) enhance behavioral financial literacy programs that focus on planning simulation, goal visualization, and self-regulation. Together, these interventions can help shift the probability of preparedness across academic populations, improving long-term financial resilience.

Limitations of this study include its modest sample size (N = 110), single-institution focus, and reliance on self-reported data, which may restrict external validity. The cross-sectional design also prevents causal inference about how preparedness evolves over time. Despite these limitations, the Bayesian framework demonstrates robustness through strong convergence diagnostics (R̂ < 1.01, ESS > 5,000), supporting the validity of probabilistic inferences.

Future research should extend this framework by employing longitudinal Bayesian updating, hierarchical models across multiple universities, and causal inference approaches that integrate psychological constructs such as time preference, optimism bias, and risk tolerance. These directions would allow scholars to map the evolution of preparedness probabilities and capture dynamic behavioral shifts before and after retirement. Moreover, expanding the model to include macroeconomic indicators (e.g., inflation expectations, pension policy reforms) could bridge micro-behavioral data with broader financial systems.

In summary, this study contributes to new knowledge in the domain of behavioral economics, financial literacy, and applied Bayesian analysis by reframing retirement preparedness as a probabilistic, multidimensional, and policy-relevant construct. It emphasizes that sustainable retirement readiness is best achieved through the synergy of institutional design, behavioral engagement, and statistical reasoning under uncertainty.

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