



Decoding the Drivers of Life Insurance Policy Preferences: A Multinomial Logistic Regression Analysis

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Article History

Received on - January 27, 2025

Revised on - April 5, 2025

Accepted on - April 28, 2025

Keywords:

Customer choice, insurance demand, life insurance, multinomial logistic regression, policy preferences

Online Access



DOI: <https://doi.org/10.58665/njiss.81>

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How to Cite APA Style

Jnawali, G., & Jaiswal, A. (2025). Decoding the drivers of life insurance policy preferences: A multinomial logistic regression analysis. *Nepalese Journal of Insurance and Social Security*, 8(1), 75-86.

Abstract

Purpose: This study investigates the socio-demographic, economic, and behavioral determinants of life insurance policy preferences in Nepal. By employing a multinomial logistic regression (MLR) framework, it examines how these factors differentially influence choices among endowment, term, and whole life insurance.

Design/methodology/approach: Using primary data from 368 policyholders in Kapilvastu district, Nepal, the study estimates an MLR model grounded in expected utility theory (EUT) and consumer choice behavior.

Findings: Age, education, income, and policy duration emerge as pivotal drivers. Endowment policies are preferred by lower-income, less-educated respondents, while term insurance appeals to younger buyers with fewer dependents. High-income individuals favor whole life insurance, reflecting long-term financial planning.

Conclusion: The research findings indicated that the elements that influence people's decisions to purchase an endowment policy rather than whole life insurance.

Implications: Insurers should segment markets by socioeconomic profiles and tailor policies to duration-sensitive buyers. Policymakers must enhance financial literacy to bridge demand gaps.

Originality/Value: This is the first study to empirically validate policy choice determinants in Nepal's understudied market, offering novel insights into behavioral heterogeneity in emerging economies.

JEL Classification: G22, C25, D12, I31

Introduction

Life insurance plays a pivotal role in risk management, wealth accumulation, and intergenerational financial protection. As a financial safety net, it mitigates the economic impact of untimely death and facilitates long-term planning. Globally, the life insurance industry has evolved from a mere mortality hedge to a multidimensional financial product embedded with investment and savings instruments (Swiss Re Institute, 2023). However, consumer choice within this domain remains surprisingly understudied, especially in terms of what drives individuals to choose among different types of life insurance policies, a critical issue for designing equitable, responsive insurance systems.

Despite innovations in life insurance products, the industry suffers from a persistent misalignment between available insurance offerings and the nuanced, often latent preferences of consumers (Cole et al., 2013). For instance, while insurers globally continue to promote bundled or complex products (like whole life or unit-linked plans), evidence shows a growing inclination among younger or economically vulnerable consumers toward simpler, lower-premium options like term insurance (Brown et al., 1993; LIMRA, 2023).



The lack of empirical insights into how and why consumers select certain policy types over others has led to supply-side inefficiencies and demand-side mistrust.

The literature presents conflicting evidence about the role of demographic and behavioral factors in shaping life insurance preferences. Some scholars argue that income and education are the most decisive variables (Beck & Webb, 2003), while others emphasize the influence of psychological constructs like risk aversion, trust, or financial literacy (Mahdzan & Victorian, 2013; Lin et al., 2017). Further inconsistency emerges around age and marital status: some studies associate age positively with whole life policy preference (Truett & Truett, 1990), whereas others suggest that younger consumers are increasingly favoring long-term investment-linked policies due to wealth accumulation motives (Outreville, 1996).

This divergence highlights a critical theoretical gap: existing studies have not sufficiently integrated socio-demographic, economic, and behavioral dimensions into a unified analytical model that explains life insurance policy choice behavior. Most research isolates variables or adopts binary logistic models focused on purchase versus non-purchase (Browne & Kim, 2023) but fails to model the competitive choice among distinct policy types, a limitation this study addresses using a multinomial logistic regression framework.

Globally, life insurance penetration remains uneven. According to Swiss Re Institute (2023), life insurance penetration in emerging Asia stands at 3.1% of GDP compared to 6.3% in advanced economies. Even more concerning is the low policy retention rate and product mismatch in South Asian markets, where 35% of policyholders discontinue their plans within the first three years (Insurance Regulatory and Development Authority of India, IRDAI, 2022). This suggests not merely a lack of coverage but a deeper issue of inappropriate policy selection.

Contrary to the argument that the absence of prior studies in a specific region constitutes a gap, this study identifies a more compelling research void: the failure of existing literature to explain the heterogeneity in consumer preferences among policy types in emerging, low-penetration insurance markets, despite the presence of different income groups, literacy levels, and cultural attitudes toward risk and family responsibility.

By modeling the determinants of life insurance policy preferences across endowment, term, and whole life plans, this study offers an integrated empirical assessment that bridges behavioral finance, consumer economics, and demographic analysis. Drawing on primary data from Nepal, an under-researched yet dynamic market, it tests a multinomial logistic regression model to reveal how socio-demographic, economic, and behavioral/policy-specific factors jointly influence decision-making.

In addition, the implications of the study are both empirical and theoretical: it not only tests established predictors in a competitive policy choice setting but also challenges the assumption of homogeneity in insurance demand. Ultimately, the findings provide actionable insights for insurance firms, policymakers, and financial educators aiming to enhance product relevance, coverage sustainability, and customer retention.

Literature Review

Life Insurance Policy Preferences Across Economies

The choice of a life insurance policy is an inherently multifaceted decision, influenced by a confluence of socio-economic, psychological, institutional, and cultural variables. Traditional economic models, most notably the EUT (Von Neumann & Morgenstern, 1944) and the Life-Cycle Hypothesis (Modigliani & Brumberg, 1954), assume that consumers are rational agents who weigh the costs and benefits of insurance to maximize lifetime utility. However, empirical research increasingly disputes the universal applicability of these models. In developed economies such as the United States, the United Kingdom, and Japan, evidence largely supports these theoretical assumptions: individuals with higher incomes, financial literacy, and risk aversion typically prefer term insurance for income replacement and whole or endowment policies for long-term financial planning (Bernheim et al., 2003; Lin & Grace, 2007). Studies have found that in these contexts, consumer choice is heavily influenced by transparent disclosures, product comprehension, and trust in regulatory mechanisms, thereby reinforcing rational decision-making frameworks. For instance, Huang et al. (2022) confirm that financial literacy and institutional confidence significantly enhance the likelihood of selecting investment-linked insurance plans.

Conversely, findings from emerging and developing markets present a more fragmented and paradoxical landscape. In countries such as India, Bangladesh, Nigeria, Indonesia, and Ghana, insurance policy decisions deviate from the predictions of EUT and instead reflect the salience of bounded rationality (Simon, 1957), heuristics, and behavioral biases (Kahneman & Tversky, 1979). In these markets, individuals with low to moderate income and education levels often gravitate toward endowment and whole life policies despite the lower returns and higher cost structures associated with these products. This phenomenon is largely driven by agent-driven sales models, information asymmetries, and a preference for policies with visible and guaranteed maturity benefits (Cole et al., 2013; Sherif & Anbar, 2016). Furthermore, cultural norms, such as patriarchal responsibilities and the desire to leave a tangible legacy, often override financial rationality. Mahdzan and Victorian (2013) argue that trust deficits in insurers and perceived claim-settlement failures disincentivize uptake of term insurance, especially in regions where insurers are viewed as extractive rather than protective institutions. Thus, while developed markets exhibit economically rational behavior consistent with theoretical models, developing markets display behavior that is institutionally and behaviorally driven, creating a theoretical divergence in explaining policy preferences.

Adding further complexity is the inconsistent influence of key demographic and socio-economic variables across regions. In developed countries, income, age, education, and family size typically exhibit linear and predictable relationships with life insurance choices (Truett & Truett, 1990; Gandolfi & Miners, 1996). However, in emerging economies, these variables often yield nonlinear and sometimes contradictory effects. For example, while higher income generally predicts term policy preference in Western markets, in South Asian contexts it may correlate with whole or endowment choices due to the perception of life insurance as a saving-cum-investment product.

Education, too, fails to produce consistent effects: in some cases, higher education leads to better-informed decisions, while in others, even educated consumers remain vulnerable to persuasive sales tactics and opaque product structures (Outreville, 2013). Furthermore, age-related trends, such as younger consumers preferring term policies, are often disrupted in developing countries, where societal expectations around familial responsibility accelerate insurance decisions at earlier life stages (Kakar & Shukla, 2010). This cross-contextual divergence not only reveals the inadequacy of applying homogeneous models of insurance behavior but also highlights the necessity for context-sensitive analyses that consider the interaction effects among institutional trust, cultural norms, and financial awareness.

It becomes evident that life insurance policy choice cannot be generalized across geographies through a singular theoretical lens. The literature calls for a shift from binary uptake models to multi-outcome frameworks, such as multinomial logistic regression models, that accommodate the diversity and complexity of consumer preferences. Despite the growing body of research, existing studies remain fragmented: some focus solely on uptake, ignoring the crucial differentiation between policy types; others isolate specific factors without integrating how they interact within broader institutional and cultural systems. Moreover, while behavioral economics has enriched the discourse, few studies operationalize these insights into statistically rigorous models capable of capturing multidimensional choice behavior. This study responds to these gaps by constructing an integrative model that examines the simultaneous effects of socio-demographic, economic, and behavioral variables on policy choice, i.e., term, whole life, and endowment, within a developing market context.

Conceptual Framework and Variable Relationships

Grounded in EUT (Friedman & Savage, 1948) and extended by contemporary consumer choice behavior theories (Browne & Kim, 1993), this study develops a multidimensional conceptual framework to explain the determinants of life insurance policy preferences. According to EUT, individuals act as rational agents who evaluate insurance policies based on their utility-maximizing potential, factoring in income, risk aversion, life expectancy, and available information. However, empirical research shows that rationality is bounded by individual characteristics, cultural norms, and institutional trust, particularly in emerging economies. The present framework integrates these theoretical insights and operationalizes key variables through a Multinomial Logistic Regression model, which allows for analyzing categorical choices among multiple policy types (El-Habil, 2012). In line with best practices in model-based research design (Sekaran & Bougie, 2016), the framework systematically categorizes variables into three domains: socio-demographic, economic, and behavioral/policy-specific.

Socio-Demographic Variables: Demographic attributes are foundational determinants in insurance decisions as they shape perceptions of financial security, risk, and social responsibility. Age plays a critical role in shaping insurance preferences. Older individuals often prioritize long-term financial stability and legacy goals, which align with whole life and endowment policies (Browne & Kim, 1993; Truett & Truett, 1990). Gender differences are equally salient—women are generally more risk-averse and may value family-oriented insurance policies more than men (Bernheim et al., 2000; Chui & Kwok, 2008). Education level, frequently correlated with

financial literacy, enhances the ability to comprehend complex policy structures and long-term benefits (Beck & Webb, 2003; Mahdzan & Victorian, 2013). Meanwhile, occupation reflects employment stability and income predictability, both of which influence the capacity to maintain long-term policy commitments (Li et al., 2007; Ghimire, 2018). Marital status further modulates these preferences, as married individuals often seek protective mechanisms for dependents, leading to a greater likelihood of opting for life insurance (Lewis, 1989; Hwang & Gao, 2003).

Economic Variables: Economic considerations serve as constraints or enablers in the insurance decision-making process. Monthly income remains a primary driver, as higher-income groups possess greater discretionary spending power and are thus more likely to purchase higher-premium or investment-linked products (Beck & Webb, 2003; Outreville, 1996). In contrast, lower-income individuals may favor endowment policies for their perceived dual benefit of protection and savings. Policy duration preference reflects risk appetite and time horizon; longer-term policies typically attract those planning for intergenerational wealth transfer or retirement security (Mahdzan & Victorian, 2013; Ghimire, 2018). Additionally, the number of dependents exerts a significant influence; households with more dependents tend to value the protective aspects of insurance more strongly, thereby increasing uptake across all policy types, especially those with guaranteed benefits (Li et al., 2007; Lewis, 1989). These economic variables interact with demographic factors, producing varied preference patterns across different population segments.

Behavioral and Policy-Specific Variables: Beyond structural determinants, behavioral elements, often underpinned by bounded rationality and heuristics, are critical in explaining insurance preferences, particularly in developing economies. Policy awareness is a key variable that reflects the consumer's informational access and comprehension of insurance options. As demonstrated by Kakar and Shukla (2010) and Mahdzan and Victorian (2013), awareness significantly correlates with policy uptake, especially among first-time buyers. Another critical factor is the influence of company agents, who often serve as primary conduits of information. In many low-trust or low-literacy contexts, agents do more than distribute products; they actively shape consumer decisions through persuasion and trust-building, frequently favoring high-commission policies over consumer-friendly ones (Sherif & Anbar, 2016; Chui & Kwok, 2008). Additionally, the number of insurance policies held by an individual serves as a proxy for insurance familiarity and experience, which can either reinforce brand loyalty or encourage diversification (Outreville, 1996; Ghimire, 2018). These behavioral variables highlight the influence of cognitive biases, informational asymmetries, and institutional trust in shaping insurance behavior.

This conceptual framework synthesizes diverse theoretical and empirical insights to propose a comprehensive model that accounts for variations in life insurance preferences across demographic, economic, and behavioral dimensions. It goes beyond simplistic binary uptake models by recognizing that individuals make nuanced choices among different policy types based on interdependent variables. The multinomial approach enables a more granular understanding of how socio-demographic factors, economic realities, and behavioral tendencies jointly influence decision-making.

Methods

Research Design and Sampling Strategy

This study adopts a descriptive and causal-comparative research design. The descriptive component aims to profile respondents based on their socio-demographic and economic characteristics, while the causal-comparative design investigates the determinants of life insurance policy choices using an MNLR model. This mixed approach is well-suited for identifying predictive patterns and generating policy-relevant insights in consumer decision-making studies.

The study population comprises individuals holding life insurance policies in the Kapilvastu district of Lumbini Province, Nepal. Due to the absence of a formal sampling frame and the requirement that respondents have prior experience with insurance decisions, a purposive sampling technique was employed. This approach aligns with exploratory research goals and allows for the identification of relevant trends (Tongco, 2007).

Based on Morgan's (1970) sample size determination table, a total of 384 structured questionnaires were distributed. Out of these, 368 were deemed valid for analysis, while 16 were excluded due to missing or inconsistent responses. Data were collected using a structured questionnaire tailored to capture socio-demographic attributes, economic indicators, and behavioral factors influencing insurance selection.

Data Analysis Techniques

Data were analyzed using IBM SPSS Version 20. The MNLR model was applied for inferential analysis. This approach is suitable for three unordered outcomes: endowment, term, and whole life insurance; the dependent variable type of insurance policy is categorical and nominal. MNLR enables one to explain the relationship between several independent variables, both categorical and continuous, and a multi-category outcome (Denham, 2017; Hosmer et al., 2013). The model projects the log-odds of selecting each policy type compared to a reference category, whole life insurance in this study.

Although mathematical formulation was discussed in brief, the focus of this research is on the practical interpretation of how socio-demographic and economic factors influence the choice of life insurance policies, therefore linking the statistical method back to the study context.

The MNLR model assumes that the independent variables might be either numerical or categorical. The dependent variable must be divided into three or more categories. There is no need for the data to have a normal distribution, a linear connection, or equal variance. MNLR is an extension of the binary logistic regression model, both of which depend on logit analysis or logistic regression. Logistic regression can be applied to models with several independent variables.

Let p be the number of predictors for a binary response Y (dependent) by the model for log odds is and the alternate formula specifies

$$\text{logit}[Y = 1] = \log \left[\frac{P(Y = 1)}{P(Y = 0)} \right] = \alpha + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \dots + \beta_p x_p$$

and the alternate formula specifies:

$$\pi(x) = \frac{e^{\alpha + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \dots + \beta_p x_p}}{1 + e^{\alpha + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \dots + \beta_p x_p}}$$

The parameter β_i relates to the effect of x_i on the log odds that $Y = 1$ while controlling x_j for instance, $\exp(\beta_i)$ is the multiplicative effect on the odds for a one-unit increase in x_i , at a fixed level of the other x_j . Now, suppose we have n independent observations with p explanatory variables, and the qualitative response variable has k categories. In that case, we must choose one of the categories as the base level and build all logits relative to it in the multinomial situation. The base level can be any category; thus, category k will be used. Since there is no ordering, thus, any category can be called k . Let $\pi_j(x_i)$ denote the multinomial probability of an observation falling in the j th category, $j = 1, 2, 3, \dots, k-1$, and $i = 1, 2, 3, \dots, n$ to find the relationship between this probability and the p explanatory variables, $x_1, x_2, x_3, x_4, \dots, x_p$, the multiple logistic regression model is used.

$$\log \left[\frac{\pi_j(x_i)}{\pi_k(x_i)} \right] = \alpha_j + \beta_{1j} x_{1i} + \beta_{2j} x_{2i} + \beta_{3j} x_{3i} + \dots + \beta_{pj} x_{pi}$$

Where, $j = 1, 2, 3, \dots, (k-1)$, $i = 1, 2, \dots, n$. Since all the π 's add to unity, this reduces to

$$\pi_j(x_i) = \frac{\exp(\alpha_j + \beta_{1j} x_{1i} + \beta_{2j} x_{2i} + \beta_{3j} x_{3i} + \dots + \beta_{pj} x_{pi})}{1 + \sum_{j=1}^{k-1} \exp(\alpha_j + \beta_{1j} x_{1i} + \beta_{2j} x_{2i} + \beta_{3j} x_{3i} + \dots + \beta_{pj} x_{pi})}, \text{ for } j = 1, 2, \dots, (k-1),$$

And the base line category

$$\pi_k(x_i) = \frac{1}{1 + \sum_{j=1}^{k-1} \exp(\alpha_j + \beta_{1j} x_{1i} + \beta_{2j} x_{2i} + \beta_{3j} x_{3i} + \dots + \beta_{pj} x_{pi})}$$

Where, $\pi_j(x_i)$ = Probability that the i th observation falls in the category j

$\pi_k(x_i)$ = Probability that the i th observation falls in the reference category k

α_j = intercept of category j

β_{ij} = Coefficient of the predictor x_i for category j

The model parameters α_j and β_{ij} are estimated using the Maximum Likelihood (ML) method. Since closed-form solutions are not available, iterative numerical methods such as Newton-Raphson or Fisher scoring algorithms are used, and modern statistical software automates this estimation process. (McCullagh & Nelder, 1989).

Results and Analysis

Demographic Profile

The study surveyed 368 participants, comprising 72% males and 28% females. The largest age group was 25–29 years, followed by 19% aged 30–34, 18.2% over 40, 16.8% aged 35–39, and 25% under 25. Most respondents were married, while 19.3% were unmarried. The majority identified as Hindu, with Muslims accounting for 15.2%. Agriculture was the most common occupation, followed by business, employment in the private sector, INGOs/NGOs, and government services. Socioeconomically, over half belonged to the middle-income group, while 35.3% were from low-income households.

Table 1: Demographic Profile of the Respondents (N = 368)

Variable	Category	Frequency	Percent (%)
Gender	Male	265	72
	Female	103	28
Age Group	Below 25 years	77	20.9
	25-29 years	92	25
	30-34 years	70	19
	35-39 years	62	16.8
	40 and above	67	18.2
Level of Education	Up to Basic Level (1-8)	147	39.9
	Secondary	162	44
	Bachelor and above	59	16
Marital Status	Married	297	80.7
	Unmarried	71	19.3
Religion	Hindu	312	84.8
	Muslim	56	15.2
Occupation	Agriculture	178	48.4
	Business	82	22.3
	Govt. Job	27	7.3
	Private Job/INGO/ NGO etc.	81	22
Economic Class	High	50	13.6
	Medium	188	51.1
	Low	130	35.3
Dependent Family Members	≤3	149	40.5
	>3	219	59.5
Monthly Income	Below 20,000	112	30.4
	20,000-29,000	115	31.3
	30,000-39,999	46	12.5
	40,000-49,999	47	12.8
	50,000 and above	48	13
Periodicity of Policy	≤15 years	214	58.2
	>15 years	154	41.8
No. of Insurance Policies	One	348	94.6
	Two	20	5.4
Type of Policy	Endowment Policy	244	66.3
	Term Insurance	30	8.2
	Whole Life Insurance	94	25.5

Most participants had more than three dependents. Monthly incomes ranged from NPR 20,000 to over NPR 50,000. Regarding insurance, the majority held a single policy with a duration of 15 years or less. Endowment policies were most common (66.3%), followed by whole life (25.5%) and term insurance (8.2%).

Multinomial Logistic Regression Analysis

MLR is suitable when the response variable comprises more than two categories, extending the binary logistic regression framework. It enables prediction based on continuous and/or categorical explanatory variables, assessing variance explained, the relative importance of predictors, interaction effects, and the influence of control variables (El-Habil, 2012). In this study, the response variable, type of insurance policy, includes three categories: endowment, term, and whole life. Predictor variables such as gender, age group, education, occupation, monthly income, number of dependents, policy periodicity, and number of policies were initially tested for association with the response variable using Chi-square tests via cross-tabulation. Only significant variables at the 5% level were included in the final MLR model. The analysis was conducted using “Whole Life Insurance” as the reference category. Model performance was evaluated using goodness-of-fit statistics, pseudo-R-squared values, and likelihood ratio tests to determine the significance and explanatory power of each predictor.

Model Fitting Information

The model fitting information indicates that the final model significantly improves over the intercept-only model, as evidenced by the likelihood ratio test (Chi-Square = 153.654, df = 38, $p < 0.001$). This suggests that the predictors collectively contribute to explaining the variation in the choice of insurance policies.

Table 2: Model Fitting Information

Model	Model Fitting Criteria			Likelihood Ratio Tests		
	AIC	BIC	-2 Log Likelihood	Chi-Square	df	p-value
Intercept Only	566.848	574.664	562.848			
Final	489.194	645.517	409.194	153.654	38	0.000

Goodness of fit, Pseudo R-Square, Classification Accuracy, and the Chance Accuracy

The goodness-of-fit statistics, including the Pearson Chi-Square (494.636, df = 454, $p = 0.091$) and Deviance (374.256, df = 454, $p = 0.997$), indicate that the model fits the data well, as the p-values are not significant, suggesting no major discrepancies between the observed and predicted values.

Table 3: Goodness of fit and Pseudo R -Square

	Goodness of Fit			Pseudo R-squared	
	Chi-Square	Df	P-value	Cox and Snell	0.341
Pearson	494.636	454	0.091	Nagelkerke	0.422
Deviance	374.256	454	0.997	McFadden	0.253

The pseudo-R-square values, Cox and Snell (0.341), Nagelkerke (0.422), and McFadden (0.253), indicate that the model explains approximately 34.1% to 42.2% of the variance in the dependent variable, demonstrating acceptable explanatory power. The model's classification accuracy rate (75.3%) exceeds the baseline chance rate (51.06%) and surpasses the 25% improvement threshold (63.83%), suggesting the model performs significantly better than random guessing (El-Habil, 2012). Additionally, all Variance Inflation Factor (VIF) values are below 5, indicating no serious multicollinearity concerns.

Table 4: Calculation of Classification Accuracy and the Chance Accuracy

Observed	Predicted: Endowment Policy	Predicted: Term Insurance	Predicted: Whole Life Insurance	Percent Correct
Endowment Policy	222	4	18	91.0%
Term Insurance	18	7	5	23.3%
Whole Life Insurance	44	2	48	51.1%
Overall Percentage	77.2%	3.5%	19.3%	75.3%

Table 5: Likelihood Ratio Tests of Predictors

Effect	Model Fitting Criteria			Likelihood Ratio Tests		
	AIC of Reduced Model	BIC of Reduced Model	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	489.194	645.517	409.194	0	0	.
Gender	485.801	634.308	409.801	0.607	2	0.738
Age Group	485.898	610.957	421.898	12.705	8	0.122
Education Level	494.017	634.708	422.017	12.823	4	0.012*
Occupation	485.107	617.982	417.107	7.913	6	0.245
Economic Class	491.022	631.713	419.022	9.828	4	0.043*
Dependent numberof family members	491.992	640.499	415.992	6.798	2	0.033*
Monthly Income	489.666	614.725	425.666	16.473	8	0.036*
Term of policy	511.916	660.423	435.916	26.722	2	0.000*
Number of insurance policies	487.161	635.668	411.161	1.967	2	0.374

Note. * = p - value < 0.05

Monthly Income ($p = 0.036$) and Periodicity of Policy ($p < 0.001$) are also significant, indicating that income levels and the duration of the policy play crucial roles in policy selection. Dependent Family Members ($p = 0.033$) is another significant factor, implying that the number of dependents influences the type of insurance policy chosen

Total Correctly Classified = $222 + 7 + 48 = 277$, Total Cases = $244 + 30 + 94 = 368$

Classification Accuracy Rate (Total Correctly Classified/Total Cases) $\times 100$

$$= (277/368) \times 100 = 75.27\%$$

The chance accuracy rate is the accuracy that would be achieved by random guessing, based on the distribution of the observed categories. It is calculated as the sum of the squares of the proportions of each category in the dataset. The proportion of each Category is computed as:

Endowment Policy: $244/368 = 0.663$, Term Insurance: $30/368 = 0.0815$ and Whole Life Insurance: $94/368 = 0.255$

$$\text{Chance Accuracy Rate} = (0.663)^2 + (0.0815)^2 + (0.255)^2$$

$$= 0.439 + 0.0066 + 0.065 = 0.5106 = 0.5106 \times 100 = 51.06\%$$

The likelihood ratio tests for individual predictors reveal that several variables significantly influence the choice of insurance policies. Specifically, Education Level ($p = 0.012$) and Economic Class ($p = 0.043$) are significant predictors, suggesting that individuals with different educational backgrounds and economic statuses have varying preferences for insurance policies.

MLR Results for Endowment Policy vs. Whole Life Insurance

At the 10% significance level, respondents aged 30-34 are considerably less likely to choose an endowment policy than those aged 40 and above (the reference category) ($p = 0.086$, Exp(B) = 0.377). Respondents with up to basic level education (1-8) are considerably more likely to choose an endowment policy than those

with a bachelor's degree or more (the reference category) at the 5% level ($p = 0.004$, $\text{Exp(B)} = 4.672$). At the 5% significance level, respondents from the high economic class are significantly less likely to select an endowment policy than those from the low economic class (the reference category). At the 5% level of significance, respondents earning 40,000-49,999 per month are significantly more likely to

choose an endowment policy than those earning 50,000 or more (the reference category). At the 5% significance level, respondents who pick a policy with a periodicity of ≤ 15 years are significantly more likely to opt for an endowment policy than those with a periodicity of > 15 years (the reference category) ($p < 0.001$, $\text{Exp(B)} = 3.467$).

Table 6: Multinomial Logistic Regression Results for Endowment Policy vs. Whole Life Insurance

Variables		B	Std. Error	Wald	df	P-value	Exp(B)	95% Confidence Interval for Exp(B)	
							Lower Bound	Upper Bound	
Intercept		0.261	1.139	0.053	1	0.819			
Gender	Male	-0.283	0.375	0.571	1	0.45	0.753	0.361	1.57
	Female	(Ref)							
Age	Below 25 years old	-0.694	0.581	1.426	1	0.232	0.499	0.16	1.561
	25-29 years old	-0.804	0.545	2.177	1	0.14	0.447	0.154	1.302
	30-34 years old	-0.976	0.568	2.946	1	0.086*	0.377	0.124	1.149
	35-39 years old	-0.727	0.618	1.386	1	0.239	0.483	0.144	1.621
	40 and above	(Ref)							
Education Level	Up to Basic Level (1-8)	1.541	0.539	8.19	1	0.004**	4.672	1.625	13.427
	Secondary	0.568	0.416	1.864	1	0.172	1.764	0.781	3.984
	Bachelor and above	(Ref)							
Occupation	Agriculture	0.592	0.457	1.677	1	0.195	1.808	0.738	4.433
	Business	-0.122	0.422	0.083	1	0.773	0.885	0.387	2.026
	Govt. Job	0.123	0.576	0.046	1	0.831	1.131	0.366	3.5
	Private Job/INGO/NGO, etc	(Ref)							
Economic Class	High	-1.771	0.677	6.852	1	0.009**	0.17	0.045	0.641
	Medium	-0.627	0.574	1.194	1	0.275	0.534	0.173	1.645
	Low	(Ref)							
Dependent Family Members	≤ 3	-0.109	0.354	0.095	1	0.758	0.897	0.448	1.795
	> 3	(Ref)							
Monthly Income	Below 20,000	-0.282	0.692	0.166	1	0.683	0.754	0.194	2.926
	20,000-29,999	0.558	0.52	1.155	1	0.283	1.748	0.631	4.839
	30,000-39,999	0.182	0.576	0.1	1	0.752	1.2	0.388	3.712
	40,000-49,999	1.165	0.553	4.438	1	0.035**	3.205	1.085	9.474
	50,000 and above	(Ref)							
Periodicity of Policy	≤ 15 years	1.243	0.325	14.61	1	0.000**	3.467	1.833	6.559
	> 15 years	(Ref)							
Number of Insurance Policies	One	0.498	0.655	0.578	1	0.447	1.645	0.456	5.935
	Two	(Ref)							

Note(s). (Ref) reference category; ** = p -value < 0.05 ; * = p -value < 0.10 , $N = 368$

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MLR Results for Term Insurance Policy vs. Whole Life Insurance At the 10% significance level, respondents aged 30-34 are considerably less likely to choose an endowment policy than those aged 40 and up (the reference category) ($p = 0.086$, $\text{Exp}(B) = 0.377$). Respondents with up to basic level education (1-8) are considerably more likely to choose an endowment policy than those with a bachelor's degree or more (the reference category) at the 5% level ($p = 0.004$, $\text{Exp}(B) = 4.672$). At the 5% significance level, respondents from the high economic class are significantly less likely

to select an endowment policy than those from the low economic class (the reference category). At the 5% level of significance, respondents earning 40,000-49,999 per month are significantly more likely to choose an endowment policy than those earning 50,000 or more (the reference category). At the 5% significance level, respondents who pick a policy with a periodicity of ≤ 15 years are significantly more likely to opt for an endowment policy than those with a periodicity of > 15 years (the reference category) ($p < 0.001$, $\text{Exp}(B) = 3.467$)

Table 7: MLR Results for Term Insurance Policy vs. Whole Life Insurance

Variable		B	Std. Error	Wald	df	p-value	Exp(B) Lower Bound	95% Confidence Interval for Exp(B)	
								Upper Bound	
Intercept		0.209	1.732	0.015	1	0.904			
Gender	Male	-0.318	0.614	0.268	1	0.605	0.728	0.218	2.425
	Female	(Ref)							
Age	Below 25 years old	-2.311	0.897	6.643	1	0.01**	0.099	0.017	0.575
	25-29 years old	-2.018	0.769	6.885	1	0.009**	0.133	0.029	0.6
	30-34 years old	-2.631	0.907	8.413	1	0.004**	0.072	0.012	0.426
	35-39 years old	-1.643	0.891	3.402	1	0.065*	0.193	0.034	1.108
	40 and above	(Ref)							
Education Level	Up to Basic Level (1-8)	0.169	0.877	0.037	1	0.847	1.184	0.212	6.602
	Secondary	-0.914	0.698	1.717	1	0.19	0.401	0.102	1.573
	Bachelor and above	(Ref)							
Occupation	Agriculture	-0.695	0.769	0.817	1	0.366	0.499	0.111	2.252
	Business	-1.371	0.739	3.442	1	0.064*	0.254	0.06	1.08
	Govt. Job	-0.63	0.895	0.495	1	0.482	0.533	0.092	3.08
	Private Job/INGO/NGO etc.	(Ref)							
Economic Class	High	-2.282	1.211	3.551	1	0.06*	0.102	0.01	1.096
	Medium	-1.299	0.959	1.832	1	0.176	0.273	0.042	1.789
	Low	(Ref)							
Dependent Family Members	≤ 3	1.19	0.573	4.318	1	0.038**	3.287	1.07	10.099
	> 3	(Ref)							
Monthly Income	Below 20,000	-2.398	1.259	3.625	1	0.057*	0.091	0.008	1.073
	20,000-29,999	-0.917	0.945	0.943	1	0.331	0.4	0.063	2.544
	30,000-39,999	-0.795	0.985	0.652	1	0.42	0.452	0.066	3.112
	40,000-49,999	1.221	0.908	1.808	1	0.179	3.39	0.572	20.09
	50,000 and above	(Ref)							
Periodicity of Policy	≤ 15 years	2.626	0.623	17.753	1	0.000**	13.824	4.074	46.903
	> 15 years	(Ref)							
Number of Insurance Policy	One	1.435	1.079	1.771	1	0.183	4.201	0.507	34.787
	Two	(Ref)							

Note(s). (Ref) reference category; ** = p - value < 0.05 ; * = p -value < 0.10 , $N = 368$

At the 10% significance level, respondents earning less than Rs. 20,000 per month are somewhat less likely to buy a term insurance policy than those earning Rs. 50,000 or more (the reference category). Other income categories do not have statistically significant effects. At the 5% significance level, respondents who choose a policy with a periodicity of ≤ 15 years are substantially more likely to opt for a term insurance policy than those with a periodicity of > 15 years (the reference category) ($p < 0.001$, $\text{Exp}(B) = 13.824$).

Discussions

The findings of this study provide empirical insights into how socio-demographic, economic, and behavioral factors influence life insurance policy preferences in the Nepalese context. Consistent with earlier studies (Outreville, 1996; Trinh et al., 2021), age emerged as a significant predictor of policy choice. Specifically, individuals aged 30–34 were significantly less likely to prefer endowment and term insurance over whole life insurance, indicating that relatively younger adults may prioritize long-term wealth accumulation and lifelong coverage over short-term financial planning. This contradicts common assumptions in emerging markets, where younger consumers are thought to favor short-term policies due to liquidity constraints (Ahmed & Ismail, 2016). The lower likelihood of choosing term insurance among younger age groups may also be driven by a lack of awareness or misperceptions about the affordability and utility of term policies (Kakar & Shukla, 2010). These findings imply the necessity for targeted awareness campaigns that emphasize the cost-effectiveness of term insurance for younger demographics.

Educational attainment also displayed a significant and nuanced impact. Respondents with up to basic education (grades 1–8) were more likely to choose endowment policies over whole life insurance, possibly due to a limited understanding of long-term investment mechanisms embedded in whole life plans. This aligns with the notion that lower education levels often correlate with lower financial literacy and limited risk tolerance, leading individuals to opt for policies with more tangible or guaranteed returns (Chui & Kwok, 2008; OECD, 2016). Conversely, individuals with bachelor's degrees or higher, who presumably possess greater financial awareness, may be more inclined to consider long-term benefits and investment-linked insurance products. This supports the broader discourse that improving financial literacy can diversify insurance uptake patterns (Lusardi & Mitchell, 2014). Given these insights, life insurance providers should consider simplifying policy presentations for lower-educated consumers while offering advisory services that demystify the value propositions of various insurance products.

Economic class and income level significantly influenced policy selection, reinforcing the findings from previous research in similar socio-economic environments (Beck & Webb, 2003; Paudel & Jha, 2019). Individuals from high-income households were significantly less likely to prefer endowment and term policies compared to their low-income counterparts. This trend could reflect the greater financial flexibility and risk appetite among higher-income groups, who may view whole life insurance as a better investment-cum-protection instrument. Conversely, individuals earning between NPR 40,000–49,999 showed a higher propensity for endowment plans, possibly due to the perception of endowment insurance as a dual-purpose product combining savings and risk coverage, a feature appealing to middle-income households striving for financial security (Ward & Zurbrugg, 2002). These findings suggest that income-based segmentation in insurance marketing could enhance product

penetration and policyholder satisfaction. Insurers may find success in bundling endowment plans with savings incentives tailored to middle-income earners.

Finally, policy periodicity strongly influenced the type of insurance chosen, with individuals opting for policies with shorter durations showing a higher likelihood of selecting endowment insurance. This aligns with the behavioral insurance literature, which indicates that time horizon and perceived liquidity significantly affect insurance product decisions (Nyman, 1999; Eisenhauer, 2000). The preference for short-period endowment policies may stem from a cultural emphasis on mid-term financial goals such as children's education or property acquisition, common among Nepalese households (Shrestha & Gautam, 2020). Additionally, behavioral factors such as hyperbolic discounting may lead individuals to undervalue the long-term benefits of whole life insurance, instead favoring products with more immediate or medium-term returns (Frederick et al., 2002). These insights reinforce the need for consumer education programs that highlight not only the cost structures but also the long-term wealth creation and protection features of whole life policies. Furthermore, insurers should consider creating hybrid products that combine the short-term appeal of endowment policies with the long-term benefits of whole life coverage to cater to evolving consumer preferences.

The findings show that age, education level, economic class, monthly income, and duration of policy are important criteria in choosing an Endowment Policy over Whole Life Insurance. Individuals with a basic education and a middle-income background are more likely to purchase endowment insurance, probably due to their simplicity and assured returns. Individuals in the upper socioeconomic class, on the other hand, are less likely to opt for endowment policies, probably due to their access to more complex financial products. Endowment preference for shorter policy durations indicates that these policies are frequently utilized to achieve medium-term financial goals, such as saving for education or retirement. The absence of significance for variables like as gender and occupation shows that these characteristics may not have a substantial influence on the decision-making process when choosing between endowment and whole life insurance.

Similarly, the findings show that age, the number of dependent family members, occupation, and policy length are the most important criteria in choosing Term Insurance over Whole Life Insurance. Younger people and those with fewer dependents are less likely to choose term insurance, whereas those who prefer shorter policy lengths are more likely to do so. These findings are consistent with previous research, which suggests that younger people and those with fewer financial dependents may prefer whole life insurance for its long-term benefits, whereas those seeking shorter-term coverage are more likely to choose term insurance (Browne and Kim, 1993; Li et al., 2007). The lack of significance for variables such as gender, education level, and occupation indicates that these characteristics may not play a significant part in the decision-making process when deciding between term and whole life insurance. However, further research with larger and more varied samples is required to verify these findings.

Conclusion and Implications

The research findings indicated that the elements that influence people's decisions to purchase an endowment policy rather than whole life insurance. Insurance companies can utilize these results to

modify their products and marketing strategies to satisfy the needs of various consumer categories. Age, education level, economic class, monthly income, and duration of policy are important criteria in choosing an Endowment Policy over Whole Life Insurance. Variables like gender and occupation do not have a substantial influence on the decision-making process when choosing between endowment and whole life insurance. The study shows that age, the number of dependent family members, occupation, and policy length are the most important criteria in choosing Term Insurance over Whole Life Insurance.

Theoretically, this study contributes to the growing literature on insurance behavior by integrating socio-demographic and behavioral economics perspectives to explain insurance preferences in an emerging economy. The findings reinforce the propositions of the Behavioral Life-Cycle Hypothesis, suggesting that individuals' temporal preferences and cognitive limitations shape financial product choices. The significant influence of education and income levels provides support for models that link financial literacy and economic capacity with insurance consumption. Furthermore, the study enriches the cross-cultural insurance literature by offering empirical evidence from Nepal, a relatively underexplored context in insurance behavior research. The use of a multinomial logistic model offers methodological rigor and provides a comparative lens across policy types, addressing a gap in earlier binary or linear approaches.

From a practical standpoint, the insights generated from this study can inform the strategic orientation of insurance providers, policymakers, and financial educators. First, insurance companies should segment their marketing strategies based on age, income, and educational profiles of target consumers. Tailored communication strategies, such as using visual aids, simplified language, and relatable case scenarios, can improve understanding among less-educated and middle-income consumers who lean toward endowment policies. Second, policy periodicity preferences reveal a latent demand for mid-term products that combine investment and protection benefits; insurers could develop hybrid insurance products to address this need. Third, the government and regulatory bodies should prioritize financial literacy campaigns to bridge knowledge gaps that prevent informed insurance decisions, especially regarding term and whole life products. Lastly, digital channels and interactive tools can be leveraged to simulate policy benefits over time, thereby increasing engagement and retention.

Limitations and Further Research

While the present study provides valuable insights, several avenues warrant future investigation. First, qualitative research employing in-depth interviews or focus groups could explore the psychological and emotional dimensions behind insurance choices, complementing the statistical insights of this study. Second, future studies could incorporate cultural dimensions, such as risk perception, family structure, and collectivist norms, to understand how social context moderates' insurance behavior in South Asia. Third, expanding the scope to include rural populations or comparisons between public and private insurance providers could reveal disparities in access and perceptions. Finally, longitudinal studies could assess how preferences evolve with changes in income, health status, and life stages, thus offering dynamic insights into policyholder behavior and product lifecycle alignment.

Acknowledgements

We would like to express our sincere gratitude to all individuals and institutions who contributed to the successful completion of this research work.

Conflict of Interest

The authors declare no conflict of interest related to this study.

Funding


This research did not receive any external funding.

Ethical Statement

This research did not require ethical approval as it does not involve any human or animal experiments.

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References

- Ahmed, N., & Ismail, Z. (2016). Determinants of life insurance demand among Malaysian consumers. *International Journal of Economics and Financial Issues*, 6(4), 185-190.
- Beck, T., & Webb, I. (2003). Economic, demographic, and institutional determinants of life insurance consumption across countries. *World Bank Economic Review*, 17(1), 51-88. DOI: [10.1093/wber/lhg011](https://doi.org/10.1093/wber/lhg011)
- Bernheim, B., Lorenzo, F., Gokhale, J., & Koltikoff, L. J. (2000). How much should Americans be saving for retirement? *American Economic Review*, 90(2), 288-292. DOI: [10.1257/aer.90.2.288](https://doi.org/10.1257/aer.90.2.288)
- Browne, M. J., & Kim, K. (1993). An international analysis of life insurance demand. *The Journal of Risk and Insurance*, 60(4), 616-634. DOI: [10.2307/253382](https://doi.org/10.2307/253382)
- Chui, A. C., & Kwok, C. C. (2008). National culture and life insurance consumption. *Journal of International Business Studies*, 39(1), 88-101. DOI: [10.1057/palgrave.jibs.8400316](https://doi.org/10.1057/palgrave.jibs.8400316)
- Cole, S., Giné, X., & Vickery, J. (2013). How does risk management influence production decisions? Evidence from a field experiment. *Review of Financial Studies*, 26(9), 2520-2553. DOI: [10.1596/1813-9450-6546](https://doi.org/10.1596/1813-9450-6546)

- Denham, B. E. (2017). *Categorical statistics for communication research*. John Wiley & Sons.
DOI: [10.1002/9781119407201](https://doi.org/10.1002/9781119407201)
- El-Habil, A. M. (2012). An application on multinomial logistic regression model. *Pakistan*
DOI: [10.18187/pjsor.v8i2.234](https://doi.org/10.18187/pjsor.v8i2.234)
- Frederick, S., Loewenstein, G., & O'Donoghue, T. (2002). Time discounting and time preference: A critical review. *Journal of Economic Literature*, 40(2), 351-401.
DOI: [10.1257/002205102320161311](https://doi.org/10.1257/002205102320161311)
- Friedman, M., & Savage, L. (1948). The Utility Analysis of Choices Involving Risk. *Journal of Political Economy*, 56(4)279-304.
DOI: [10.1086/256692](https://doi.org/10.1086/256692)
- Gandolfi, A. S., & Miners, L. (1996). Gender based differences in life insurance ownership. *Journal of Risk and Insurance*, 63(4),683-693.
DOI: [10.2307/253478](https://doi.org/10.2307/253478)
- Ghimire, B. (2018). Determinants of life insurance demand in Nepal. *Journal of Business and Social Sciences*, 6(1), 45-54.
- Giné, X., Townsend, R. M., & Vickery, J. I. (2008). Patterns of rainfall insurance participation in rural India. *World Bank Economic Review*, 22(3), 539-566.
DOI: [10.1093/wber/lhn005](https://doi.org/10.1093/wber/lhn005)
- Hosmer, D.W., Lemeshow, S., & Sturdivant, R. X. (2013). *Applied Logistic Regression* (3rd ed.). Wiley.
DOI: [10.1002/9781119407201.ch7](https://doi.org/10.1002/9781119407201.ch7)
- Huang, W., Yu, J., & Hu, T. (2022). Financial literacy and life insurance uptake: Evidence from emerging markets. *Asian Economic Journal*, 36(1), 25-47.
- Hwang, T., & Gao, S. (2003). The determinants of demand for life insurance in an emerging economy-The case of China. *Managerial Finance*, 29(5/6):82-96.
DOI: [10.1108/03074350310768779](https://doi.org/10.1108/03074350310768779)
- Insurance Regulatory and Development Authority of India. (2022). *Annual report 2021-22*. New, Delhi, India
- Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, 47(2), 263-291.
DOI: [10.2307/1914185](https://doi.org/10.2307/1914185)
- Kakar, P., & Shukla, R. (2010). The determinants of demand for life insurance in an emerging economy-India. *The Journal of Applied Economic Research*, 4(1),49-77
DOI: [10.1177/097380100900400103](https://doi.org/10.1177/097380100900400103)
- Lewis, F. D. (1989). Dependents and the demand for life insurance. *American Economic Review*, 79(3), 452-466.
- Li, D., Moshirian, F., Nguyen, P., & Wee, T. (2007). The demand for life insurance in OECD countries. *The Journal of Risk and Insurance*, 74(3),637-652.
DOI: [10.1111/j.1539-6975.2007.00228.x](https://doi.org/10.1111/j.1539-6975.2007.00228.x)
- Life Insurance Marketing and Research Association. (2023). 2023 global insurance outlook: The shift toward simplicity [Industry report]. LIMRA.
- Lin, C., Hsiao, Y. J., & Yeh, C. Y. (2017). Financial literacy, financial advisors, and information sources on demand for life insurance. *Pacific-Basin Finance Journal*, 43, 218-237.
DOI: [10.1016/j.pacfin.2017.04.002](https://doi.org/10.1016/j.pacfin.2017.04.002)
- Lin, X., Liu, Y., & Deng, X. (2017). Risk preference, trust, and insurance demand: Evidence from China. *Emerging Markets Finance and Trade*, 53(10), 2292-2307.
DOI: [10.1080/1540496X.2017.1284658](https://doi.org/10.1080/1540496X.2017.1284658)
- Lin, Y., & Grace, M. F. (2007). Household life insurance demand: An empirical study using household data. *Journal of Risk and Insurance*, 74(1), 27-4
DOI: [10.1111/j.1539-6975.2007.00205.x](https://doi.org/10.1111/j.1539-6975.2007.00205.x)
- Lusardi, A., Mitchell, O. S., & Curto, V. (2010). Financial Literacy among the Young. *The Journal of Consumer Affairs*, 44(2),358-380.
DOI: [10.1111/j.1745-6606.2010.01173.x](https://doi.org/10.1111/j.1745-6606.2010.01173.x)
- Mahdzan, N. S., & Victorian, S. P. (2013). The determinants of life insurance demand: A focus on saving motives and financial literacy. *Asian Social Science*, 9(5), 274.
DOI: [10.5539/ass.v9n5p274](https://doi.org/10.5539/ass.v9n5p274)
- McCullagh, P., & Nelder, J. A. (1989). *Generalized Linear Models* (2nd ed.). Chapman & Hall.
DOI: [10.1007/978-1-4899-3242-6](https://doi.org/10.1007/978-1-4899-3242-6)
PMCID: PMC1385319
- Modigliani, F., & Brumberg, R. (1954). Utility analysis and the consumption function: An interpretation of crosssection data. In K. K. Kurihara (Ed.), *Post-Keynesian economics* (pp. 388-436). Rutgers University Press.
- Morgan, D. W. (1970). Determining sample size for research. *Educational and Psychological measurement*, 30,607-610.
DOI: [10.1177/001316447003000308](https://doi.org/10.1177/001316447003000308)
- Organisation for Economic Co-operation and Development (2016). OECD/INFE international survey of adult financial literacy competencies. <https://www.oecd.org/finance/oecd-infe-survey-adult-financial-literacy-competencies.htm>

- Outreville, J. F. (1996). Life Insurance in Developing Countries. *Journal of Risk and Insurance*, 63(2), 263-278.
DOI: [10.2307/253745](https://doi.org/10.2307/253745)
- Outreville, J. F. (2013). The relationship between relative risk aversion and the level of Economic Surveys, 29(1), 97-111.
DOI: [10.1111/joes.12050](https://doi.org/10.1111/joes.12050)
- education: A survey and implications for the demand for life insurance. *Journal of Economic Surveys*, 29(1), 97-111.
DOI: [10.1111/joes.12050](https://doi.org/10.1111/joes.12050)
- Sekaran, U., & Bougie, R. (2016). Research methods for business: A skill building approach. John Wiley & Sons.
- Sherif, M., & Anbar, A. (2016). Determinants of demand on family Takaful in Egypt: A marketing perspective. *International Journal of Islamic Marketing and Branding*, 1(3), 215-232.
- Shrestha, P., & Gautam, R. (2020). Financial planning and life insurance behavior in Nepalese households. *Nepalese Journal of Management Science and Research*, 3(1), 45-58.
- Simon, H. A. (1957). Models of man: Social and rational. Wiley.
DOI: [10.2307/2550441](https://doi.org/10.2307/2550441)
- Swiss Re Institute (2023). World insurance: Inflation risks ahead - Sigma Report No. 4/2023. <https://www.swissre.com/institute/research/sigma-research/sigma-2023-04.html>
- Tongco, M. D. C. (2007). Purposive sampling as a tool for informant selection. *Ethnobotany Research and Applications*, 5, 147-158.
DOI: [10.17348/era.5.0.147-158](https://doi.org/10.17348/era.5.0.147-158)
- Trinh, H., Pham, T., & Nguyen, V. (2021). Insurance awareness and policy choice: Evidence from Southeast Asia. *Asian Journal of Insurance Studies*, 5(2), 121-135.
- Truett, D., & Truett, L. (1990). The demand for life insurance in Mexico and the United States: A comparative study. *Journal of Risk and Insurance*, 57(2), 321-328.
DOI: [10.2307/253306](https://doi.org/10.2307/253306)
- Von Neumann, J., & Morgenstern, O. (1944). Theory of games and economic behavior. Princeton University Press.
- Ward, D., & Zurbrugg, R. (2002). Law, politics and life insurance consumption in Asia. *The Geneva Papers on Risk and Insurance*, 27(3), 395-412.
DOI: [10.1111/1468-0440.00181](https://doi.org/10.1111/1468-0440.00181)

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