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Behavioural Biases and Demographic Dynamics: Unraveling the Determinants of Life Insurance Purchase Intentions

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KEYWORDS

Behavioural biases, Life insurance, financial decision-making, loss aversion, low-income groups.

ABSTRACT

This study examines the impact of behavioural biases and demographic characteristics on life insurance purchase intentions. The research highlights how cognitive factors such as overconfidence, loss aversion, social norms, and hyperbolic discounting influence financial decision-making and how these effects are moderated by age, gender, and education. A quantitative research design was employed using survey data from 509 urban respondents, especially those from lower income group or unorganized sector. Hierarchical multiple regression analysis was applied to assess the direct effects of behavioural biases on life insurance purchase intentions and the moderating role of demographic variables. The study leverages prospect theory and behavioural economics to interpret consumer decision-making patterns. The findings indicate that overconfidence negatively impacts life insurance purchase intention, while loss aversion and social norms positively influence it. Hyperbolic discounting shows a marginal negative effect. Additionally, demographic factors moderate these relationships, with higher education mitigating overconfidence, age reducing its negative impact, and social norms influencing women's purchase intentions more significantly than men's. Findings suggest that insurers should develop targeted financial education programs to mitigate overconfidence and enhance consumer awareness. Marketing strategies can leverage social norms to improve insurance adoption, particularly among women. Customized insurance products and incentives addressing behavioural biases may enhance policy uptake.

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1. INTRODUCTION

Life insurance provides financial protection to dependents in the event of the policyholder's death. Uptake and penetration of life insurance play a crucial role in the growth of an economy (Horvey et al., 2024). Life insurance is positively correlated with economic development and growth (Nasri et al., 2024). A strong insurance industry becomes more necessary as nations expand and diversify, emphasizing its critical role in the overall well-being and success of the economy(Dawd & Benlagha, 2023).

Despite its importance, life insurance adoption is influenced by demographic, socioeconomic, and behavioural factors. Understanding these influences is critical for consumers making informed choices and for insurers designing effective products and marketing strategies. Besides, underinsurance remains a significant issue, particularly in developing economies, driven by economic constraints, psychological biases, and social influences. This study examines how demographic factors and behavioural biases shape life insurance purchase intentions. Ironically, the segment (low income/ unorganized) of the society which needs life insurance the most is the least covered. Despite being the most exposed to financial instability caused by unanticipated catastrophes, these groups often lack proper insurance coverage. According to the International Labour Organization (ILO), major coverage gaps continue in social security systems, especially in low-income countries where public spending and access to health care are limited (ILO, 2020). This coverage gap highlights the need of targeted actions that extend insurance benefits to marginalized communities.

Behavioural economics challenges the assumption that financial decisions are purely rational. Traditional models suggest decision-makers optimize utility based on available information, yet cognitive biases and heuristics frequently distort these choices (Thaler & Sunstein, 2008). Overconfidence, for instance, leads individuals to underestimate risks, reducing their perceived need for life insurance (Barber & Odean, 2001). Conversely, loss aversion—where losses weigh more heavily than equivalent gains (Kahneman & Tversky, 1979)—can motivate insurance purchases to mitigate perceived financial risks. Social norms further influence decisions, particularly in collectivist cultures, where life insurance is perceived as a responsible financial safeguard (Cialdini & Trost, 1998). Meanwhile, hyperbolic discounting, the preference for immediate rewards over long-term benefits, may delay life insurance adoption, exacerbating underinsurance (Laibson, 1997).

Demographics interact with behavioural biases, amplifying or mitigating their effects. Younger individuals often delay life insurance due to lower perceived risk, though overconfidence and hyperbolic discounting may further discourage early adoption (Lusardi & Mitchell, 2007). Gender differences also play a role; while men have traditionally held more insurance as primary earners, shifting economic roles are narrowing this gap (Bernasek & Shwiff, 2001). Education significantly impacts life insurance consumption (Srinivasan & Mitra, 2024).Education enhances financial literacy, reducing susceptibility to short-term biases and improving risk assessment, while also moderating overconfidence (Lusardi & Mitchell, 2014). Higher-income individuals, with greater financial responsibilities, exhibit stronger loss aversion, making them more likely to secure life insurance (Bernheim, 1991). There exists a positive wealth-insurance correlation, with less wealthy individuals having lesser life-insurance coverage (Gropper & Kuhnen, 2021).

Given the complex interplay of these factors, a purely individual or isolated approach to understanding life insurance decisions is insufficient. This study addresses this gap by adopting an interactional model that considers the simultaneous effects of demographics and behavioural biases. By analyzing these interaction effects, this research provides deeper theoretical insights into financial decision-making and offers practical implications for insurers and policymakers seeking to enhance insurance uptake and financial security.

2. RESEARCH OBJECTIVES

The Study analyses how demographics (Age, Gender, Education) and behavioural biases (Overconfidence, Loss Aversion, Social Norms, Hyperbolic Discounting) impact life insurance purchasing intentions in the economically weaker sections.

1. Identify the main effects of behavioural factors on life insurance purchase intention.
2. Investigate the moderating effects of demographic variables on these relationships.
3. Refine the interaction model to focus on statistically significant interactions that provide the best fit for the data.
4. Offer practical recommendations for insurers on how to tailor their products and marketing strategies based on the identified interactions.

By achieving these objectives, this study contributes to the growing body of literature on behavioural finance and provides actionable insights for the life insurance industry.

3. LITERATURE REVIEW

Life insurance purchasing decisions result from complex interactions between behavioural biases and demographic factors. While behavioural economics has extensively studied financial decision-making, its application to insurance choices remains underexplored. Overconfidence, a well-documented cognitive bias, leads individuals to underestimate risks and perceive less need for financial protection (Barber & Odean, 2001). While extensively studied in investment behavior (Daniel et al., 1998), its role in insurance decisions remains underexamined, particularly in interaction with age and education. Younger individuals tend to be more overconfident (Hvide, 2002), yet the extent to which education mitigates this bias in life insurance choices is unclear.

Loss aversion, where individuals prioritize avoiding losses over equivalent gains (Kahneman & Tversky, 1979), is a strong predictor of insurance demand (Braun & Muermann, 2004). However, its interaction with income and financial literacy remains insufficiently studied. Wealthier individuals, who can better absorb financial shocks, may exhibit lower insurance demand (Bernheim, 1991), while financial literacy may moderate loss aversion by improving understanding of insurance benefits (Lusardi & Mitchell, 2014).

Social norms shape financial decisions, particularly in collectivist cultures where insurance is viewed as a responsible act of protecting loved ones (Cialdini & Trost, 1998; Botzen et al., 2009). However, research on how gender and cultural influences shape these norms in insurance decisions is limited. While gender roles may amplify normative pressure (Bernasek & Shwiff, 2001), the extent of this effect across different cultural settings remains an open question.

Hyperbolic discounting, the tendency to prioritize immediate rewards over long-term benefits (Laibson, 1997), discourages insurance adoption due to its delayed payoffs (Ashraf et al., 2006). While extensively studied in retirement savings (O'Donoghue & Rabin, 1999), its role in insurance decisions, particularly its interaction with age and education, remains unclear. Older individuals, more attuned to long-term financial security, may be less prone to this bias (Goda et al., 2014), but empirical evidence is lacking.

Age influences insurance uptake, with younger individuals perceiving lower immediate risk and having fewer dependents (Lusardi & Mitchell, 2007). However, research has not sufficiently explored how behavioural biases such as overconfidence and hyperbolic discounting shape these age-related trends. Similarly, while gender differences in risk perception and financial decisions are well established (Eckel & Grossman, 2008), studies rarely examine how behavioural biases differentially affect men's and women's insurance choices.

Education enhances financial literacy and reduces susceptibility to cognitive biases (Lusardi & Mitchell, 2014), potentially mitigating the effects of hyperbolic discounting and overconfidence (Peters et al., 2006). However, its precise role in life insurance adoption remains underexplored. Higher education may encourage better risk assessment, but whether it moderates biases or interacts differently across income levels is unclear.

Income and information are positively correlated with life-insurance possession(Methasani et al., 2025) .Income significantly influences insurance affordability and financial priorities (Bernheim, 1991), yet its interaction with behavioural biases remains understudied. Loss aversion may be stronger among lower-income individuals who face higher financial insecurity (Hoffmann & Post, 2014), while hyperbolic discounting may lead them to prioritize short-term needs over long-term security (Ashraf et al., 2006). These dynamics require further empirical validation.

Further, Despite the rising literature on consumer behavior in life insurance purchases, there are substantial gaps in understanding the purchasing intents of lower and middle-income groups, as well as unorganized sector workers. Existing research focuses mostly on higher-income persons with better financial literacy, structured work perks, and access to advisory services (Giesbert et al., 2011; Outreville, 2015). However, lower and middle-income customers often display distinct behavioural biases, risk perceptions, and affordability restrictions that influence their insurance choices (Cole et al., 2013). Furthermore, the unorganized sector, which accounts for a sizable proportion of the workforce in developing nations, is frequently overlooked in insurance studies (Banerjee et al., 2014). These groups may have unique trust difficulties, financial planning goals, and digital adoption hurdles that current insurance adoption models do not account for (Kumar et al., 2020). The scarcity of empirical studies concentrating on these underrepresented groups presents a crucial research vacuum, impeding the development of inclusive insurance frameworks that meet their requirements. Future study should look at the behavioural, socioeconomic, and technical factors that influence insurance uptake, resulting in a more thorough knowledge of life insurance penetration and financial security across different consumer groups (Matul et al., 2013).

Extensive research has been accomplished on behavioural economics and financial decision-making, the interplay between demographics and behavioural biases in life insurance decisions remains largely unexplored. Most studies examine these factors in isolation rather than considering their interactive effects. Overconfidence in insurance adoption, particularly moderated by age and education, remains understudied. While loss aversion is a key driver of insurance demand, its dependence on financial literacy and income needs further examination. Cultural influences on social norms and gendered insurance behavior require greater focus, particularly in non-Western contexts. Finally, hyperbolic discounting's role in delaying insurance purchases, especially among younger and less-educated individuals, warrants deeper investigation.

4. RELEVANCE OF THE STUDY

This study examines life insurance purchasing intentions by analyzing the interaction between demographic factors and behavioural biases, addressing key gaps in the literature. It contributes to behavioural economics and financial decision-making by revealing how individual traits shape insurance choices. The study would also be relevant for increasing insurance coverage in economically weaker sections.

The findings have significant industry implications. Understanding how biases vary across demographic groups can help insurers tailor products and marketing strategies more effectively. Identifying populations most susceptible to biases enables targeted interventions to improve financial decision-making.

Policymakers can also leverage these insights to design financial education programs that mitigate biases and improve insurance coverage in low-income groups. Initiatives for younger individuals may focus on overconfidence and hyperbolic discounting, while those for older populations can emphasize long-term financial security. By exploring the interplay of demographics and behavior, this research advances academic theory and informs industry practice, offering a more comprehensive understanding of life insurance adoption.

5. RESEARCH METHODOLOGY

This study examines how demographic factors (age, gender, education, income) and behavioural biases (overconfidence, loss aversion, social norms, hyperbolic discounting) influence life insurance purchase intentions. A cross-sectional, quantitative approach was employed to ensure precise variable measurement and hypothesis testing (Creswell, 2014).

A structured survey was administered to 509 urban adults (18+), focusing on lower and lower-middle-income groups in Delhi and the National Capital Region. Convenience sampling was used due to time and cost constraints, despite potential bias (Etikan et al., 2016). Data collection included both online and in-person responses to enhance sample diversity.

Multiple regression analysis was applied, exceeding the recommended sample size for statistical power (Field, 2018). The questionnaire, pilot-tested on 35 respondents, measured behavioural biases, demographics, and insurance purchase intentions. Minor revisions were made for clarity and reliability before full deployment.

Operationalization of Variables

Independent Variables (Behavioural Biases)

- **Overconfidence:** Overconfidence was examined using a four-item scale developed from Lin (2011) to assess participants' confidence level regarding life insurance.. Example: “I am sure that I don’t need life insurance.” On a seven-point Likert scale, responses ranged from 1 (Strongly Disagree) to 7 (Strongly Agree).
- **Loss Aversion:** A six-item scale based on Li, J., Chai, L., Nordstrom, O., Tangpong, C., & Hung, K.-T. (2021) assessed loss aversion. The scale measures participants' financial decision-making sensitivity to losses, such as “I do not feel comfortable about taking chances.” Responses were on a 7-point Likert scale.
- **Social Norms:** A four-item scale derived from Meister, H., Grugel, L., & Meis, M. (2014) measured perceived social pressure to buy life insurance. Examples include “People important to me think I should have life insurance.” Responses were on a 7-point Likert scale.
- **Hyperbolic Discounting:** A three-item scale derived from Kang, M. Il, & Ikeda, S. (2016) assessed degree of impatience and hyperbolic discounting. With questions like “Receive Rs. 1000 today OR Rs.____ in a week”, the scale measures participants' desire for immediate incentives versus future advantages. The responses were utilized for calculation of α, degree of declining impatience, as a measure of present bias, Kang, M. Il, & Ikeda, S. (2016).

Moderating Variables (Demographic Factors)

- **Age:** Participant were asked to choose the age interval they belonged to.
- **Gender:** The categorical variable gender was Male (coded 1) or Female (2). Non-binary and prefer-not-to-say choices were available but underrepresented in the main study.
- **Education:** Education was measured as an ordinal variable, capturing the highest level of education attained by the participant, ranging from 1 (Never educated) to 8 (Doctorate).
- **Household Income:** Household income was measured as an ordinal variable, capturing the total monthly household income on a scale from 1 (Less than Rs. 10,000) to 5 (More than Rs. 100,000).

Dependent Variable (Life Insurance Purchase Intention)

A three-item scale derived from Botzen, Aerts, and van den Bergh (2009) assessed life insurance purchase intention. With answers like “I intend to purchase life insurance within the next year,” the scale measures the possibility of buying life insurance soon. Responses were on a 7-point Likert scale.

Interaction Terms

Interaction terms were established to study how demographic characteristics modify behavioural biases and life insurance purchasing intention. The interaction terms were calculated by multiplying the centered scores of each behavioural bias with the centered scores of each demographic variable (e.g., Overconfidence x Age, Loss Aversion x Income). Centring reduced multicollinearity and improved interaction effect interpretation (Aiken & West, 1991).

Data Analysis Techniques

Hierarchical multiple regression was used to examine how distinct sets of factors predict a dependent variable (Tabachnick & Fidell, 2013). Hierarchical regression tests main effects, interaction effects, and moderates variable correlations, hence it was selected.

Preliminary Analysis

Prior to conducting the regression analysis, data cleaning and screening were performed to address missing data, outliers, and assumptions of normality, linearity, and homoscedasticity. Missing data were handled using multiple imputation, a method that generates several complete datasets by imputing missing values based on observed data (Rubin, 1987). Outliers were identified using standardized residuals and removed if they exceeded ±3 standard deviations from the mean (Field, 2018).

Main Analysis

The hierarchical regression analysis has three steps:

- **Step 1**: The major impact of independent factors (Overconfidence, Loss Aversion, Social Norms, Hyperbolic Discounting) on life insurance purchase intention was modeled.
- **Step 2**: Demographic factors (Age, Gender, Education, Household Income) were analyzed to determine their impact on life insurance purchase intention.
- **Step 3**: Interaction terms were used to analyze how demographic characteristics moderate the link between behavioural biases and life insurance purchase intention.

The statistical significance of the interaction coefficients and the change in R-squared values between stages were used to evaluate the interaction terms. A substantial interaction term suggests that demographic variable level affects behavioural bias on life insurance purchasing intention.

Hypotheses Tested

The research evaluated these hypotheses:

H1: Overconfidence reduces life insurance buying intention.

H2: Loss aversion increases life insurance purchasing intention

H3: Social norms increase life insurance buying intention.

H4: Hyperbolic discounting has a negative impact on life insurance purchase intention.

H5: Age moderates the relationship between overconfidence and life insurance purchase intention, such that the negative impact of overconfidence is stronger among younger individuals.

H6: Education moderates the relationship between overconfidence and life insurance purchase intention, such that the negative impact of overconfidence is weaker among more educated individuals.

H7: Gender moderates the relationship between social norms and life insurance purchase intention, such that the positive impact of social norms is stronger among women.

H8: Education moderates the relationship between hyperbolic discounting and life insurance purchase intention, such that the negative impact of hyperbolic discounting is weaker among more educated individuals.

Ethical Considerations

This study adhered to ethical guidelines for research involving human participants. Informed consent was obtained from all participants before they completed the questionnaire. Participants were informed about the purpose of the study, the voluntary nature of their participation, and their right to withdraw at any time without penalty. Anonymity and confidentiality of participants' responses were maintained throughout the study.

Validity and Reliability

Construct Validity: Construct validity is how well measuring tools assess their intended constructs (Cronbach & Meehl, 1955). Overconfidence, loss aversion, social norms, hyperbolic discounting, and life insurance purchase intention questionnaire was developed from prior research to assure construct validity. Each scale was subjected to factor analysis to confirm its unidimensionality and to ensure that it measured a single construct (Tabachnick & Fidell, 2013).

Reliability: The consistency of a measuring instrument's findings across several trials is called reliability (Nunnally & Bernstein, 1994). Cronbach's alpha was used to examine each scale's internal consistency, with a 0.70 level regarded adequate for study (George & Mallery, 2019). All scales had great reliability, with Cronbach's alpha values from 0.75 to 0.89.

External Validity: External validity measures how well the results apply to different contexts, people, and timeframes (Campbell & Stanley, 1963). Although convenience sampling restricts generalizability, a diversified sample in age, gender, education, and income was used to improve external validity. The conclusions apply largely to urban areas where life insurance is available.

The study utilizes a cross-sectional survey design with hierarchical regression analysis to test the hypothesized relationships and interactions. By addressing the gaps identified in the literature, this research contributes to a deeper understanding of the factors influencing life insurance decisions and offers valuable insights for both academic research and practical applications in the insurance industry.

Data Analysis

Hierarchical multiple regression tested the main impacts of independent variables and demographic factors' moderating effects. The analytical equations and findings are detailed.

Preliminary Data Screening and Descriptive Statistics

Missing values, outliers, normalcy, linearity, and multicollinearity assumptions were tested before main analysis. The approach included multiple imputation for missing data, outlier detection using standardized residuals, and removal of cases beyond ±3 standard deviations (Field, 2018). Final analytical sample: 509.

Table I presents the descriptive statistics for the key variables, including means, standard deviations, and correlations among the variables. The correlations were checked to ensure that multicollinearity was not a concern, with variance inflation factors (VIFs) all falling below the commonly accepted threshold of 10 (Tabachnick & Fidell, 2013).

Table I

Table I Descriptive Statistics and Correlation Matrix

Variable	M	SD	1	2	3
1. Overconfidence	3.45	0.72	1.00		
2. Loss Aversion	3.82	0.68	.22**	1.00	
3. Social Norms	3.65	0.76	.18**	.24**	1.00

Note. *p* < .05, **p** < .01.

Table II

Table II Demographic distribution of the respondents

Age	
18-24	121
25-34	230
35-44	94
45-54	43
55 and above	21
Total	509
Gender	
Male	301
Female	208
Total	509

Marital and Family Status	
Single	131
Married without Children	44
Married with Dependent Children	292
Married with Independent Children	42
Total	509
Education	
Never educated	112
Non-Matriculated	84
High-School	88
Diploma	13
Intermediate (10+2)	78
Bachelor's Degree	92
Professional/ Master's Degree	42
Doctorate	0
Total	509
Household Income	
Less than Rs. 10,000 / Month	276
Rs. 10,000 – 25,000 / Month	160
Rs. 25,001 – 50,000 / Month	56
Rs. 50,001 – 100,000 / Month	5
More than Rs. 1 Lakh / Month	12
Total	**509**

Hierarchical Regression Analysis

Three-step hierarchical multiple regression was used to evaluate the main impacts of independent variables, demographic variables, and behavioural biases and demographic factors on life insurance purchase intentions. Hierarchical regression equation in general:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \varepsilon$$

Where:

- Y = Life insurance purchase intention
- β_0 = Intercept
- $\beta_1,\beta_2,\ldots,\beta_n$ = Regression coefficients for predictors
- $X_1,X_2,\ldots,X_n$ = Predictor variables (including interaction terms)
- ϵ = Error term

Step 1: Main Effects Model

The first step involved entering the main effects of the behavioural biases (Overconfidence, Loss Aversion, Social Norms, Hyperbolic Discounting) into the regression model. The equation for the main effects model is as follows:

$$\text{Purchase Intention}=\beta_0+\beta_1(\text{Overconfidence})+\beta_2(\text{Loss Aversion})+\beta_3(\text{Social Norms})+\beta_4(\text{Hyperbolic Discounting})+\epsilon$$

Table III

Table III Main Effects Regression Results

Predictor	**B**	**SE**	**β**	**t**	**P**
(Intercept)	2.734	0.172		15.896	.000
Overconfidence	-0.317	0.054	-.285	-5.852	.000
Loss Aversion	0.220	0.073	.187	3.014	.003
Social Norms	0.375	0.062	.342	6.048	.000
Hyperbolic Discounting	-0.136	0.071	-.112	-1.915	.056

Note. R^2 = .170, Adjusted R^2 = .164, $F(4, 504)$ = 25.87, p < .001

Interpretation: The main effects model explains 17.0% of the variance in life insurance purchase intention. Overconfidence ($\beta=-0.317, p<.001$), Loss Aversion ($\beta=0.220, p=.003$), and Social Norms ($\beta=0.375, p<.001$) were all significant predictors. Hyperbolic Discounting showed a marginal negative effect ($\beta=-0.136, p=.056$).

Step 2: Adding Demographic Variables

In the second step, demographic variables (Age, Gender, Education, Household Income) were added to the model to assess their effects on life insurance purchase intention. The equation for this model is:

$$\text{Purchase Intention}=\beta_0+\beta_1(\text{Overconfidence})+\beta_2(\text{Loss Aversion})+\beta_3(\text{Social Norms})+\beta_4(\text{Hyperbolic Discounting})+\beta_5(\text{Age})+\beta_6(\text{Gender})+\beta_7(\text{Education})+\beta_8(\text{Income})+\epsilon$$

Table IV

Table IV Regression Results with Demographic Variables

Predictor	**B**	**SE**	**β**	**t**	**p**
(Intercept)	2.516	0.231		10.893	.000
Overconfidence	-0.289	0.052	-.260	-5.558	.000
Loss Aversion	0.196	0.072	.167	2.727	.007
Social Norms	0.356	0.061	.325	5.836	.000

Predictor	B	SE	β	t	p
Hyperbolic Discounting	-0.124	0.069	-.102	-1.797	.073
Age	-0.032	0.008	-.156	-4.058	.000
Gender	0.097	0.094	.048	1.030	.303
Education	0.153	0.039	.134	3.916	.000
Household Income	0.143	0.032	.174	4.469	.000

Note. $R^2 = .276$, Adjusted $R^2 = .260$, $F(8, 500) = 23.76$, $p < .001$.

Interpretation: Adding demographic variables increased the explanatory power of the model to 27.6%. Age ($\beta=-0.032, p<.001$), Education ($\beta=0.153, p<.001$), and Household Income ($\beta=0.143, p<.001$) emerged as significant predictors, while Gender did not significantly affect life insurance purchase intention. The inclusion of demographic variables significantly improved the model fit, as evidenced by the increase in R^2 from 17.0% to 27.6% ($\Delta R^2=0.106$, $p<.001$).

Step 3: Interaction Effects Model

In the third step, interaction terms between the behavioural biases and demographic variables were introduced into the model to examine the moderating effects of demographics on the relationship between behavioural biases and life insurance purchase intention. The equation for the interaction model is:

$$\text{Purchase Intention}=\beta_0+\beta_1(\text{Overconfidence})+\beta_2(\text{Loss Aversion})+\beta_3(\text{Social Norms})+\beta_4(\text{Hyperbolic Discounting})+\beta_5(\text{Age})+\beta_6(\text{Gender})+\beta_7(\text{Education})+\beta_8(\text{Income})+\beta_9(\text{Overconfidence}\times\text{Education})+\beta_{10}(\text{Social Norms}\times\text{Gender})+\beta_{11}(\text{Overconfidence}\times\text{Age})+\epsilon$$

Table V

Table V Regression Results with Interaction Effects

Predictor	B	SE	β	t	p
(Intercept)	2.358	0.241		9.789	.000
Overconfidence	-0.287	0.051	-.258	-5.647	.000
Loss Aversion	0.191	0.070	.163	2.711	.007
Social Norms	0.349	0.061	.318	5.714	.000
Hyperbolic Discounting	-0.119	0.068	-.098	-1.750	.081
Age	-0.035	0.008	-.171	-4.351	.000

Predictor	B	SE	β	t	p
Gender	0.104	0.092	.052	1.130	.259
Education	0.142	0.039	.124	3.641	.000
Household Income	0.139	0.031	.170	4.463	.000
Overconfidence × Education	0.072	0.019	.132	3.789	.000
Social Norms × Gender	-0.347	0.134	-.106	-2.591	.010
Overconfidence × Age	0.132	0.041	.112	3.220	.001

Note. $R^2 = .340$, Adjusted $R^2 = .307$, $F(11, 497) = 10.73$, $p < .001$.

Interpretation: The introduction of interaction terms further increased the model's explanatory power, with R^2 rising to 34.0% ($\Delta R^2=0.064$, $p<.001$). The significant interaction terms suggest that the effects of certain behavioural biases on life insurance purchase intention are moderated by demographic factors. Specifically:

- **Overconfidence × Education:** The positive interaction term ($\beta=0.072$, $p<.001$) indicates that the negative impact of overconfidence on life insurance purchase intention is attenuated as education increases. More educated individuals are likely better equipped to recognize the importance of life insurance, thus mitigating the overconfidence bias.
- **Social Norms × Gender:** The negative interaction term ($\beta=-0.347$, $p=.010$) suggests that the positive influence of social norms on life insurance purchase intention is less pronounced for one gender (possibly males), reflecting varying degrees of susceptibility to social influences between genders.
- **Overconfidence × Age:** The positive interaction term ($\beta=0.132, p=.001$) suggests that the negative effect of overconfidence on life insurance purchase intention decreases with age. Older individuals may gain more life experience and awareness of risk, thereby counteracting the effects of overconfidence.

Summary of Hypotheses Testing

The results of the hierarchical regression analysis support several of the hypotheses tested in the study:

- **H1 (Overconfidence negatively impacts life insurance purchase intention):** Supported. Overconfidence consistently showed a negative relationship with life insurance purchase intention across all models.
- **H2 (Loss Aversion positively impacts life insurance purchase intention):** Supported. Loss aversion was a significant positive predictor of life insurance purchase intention.
- **H3 (Social Norms positively impact life insurance purchase intention):** Supported. Social norms were a strong positive predictor of life insurance purchase intention.
- **H4 (Hyperbolic Discounting negatively impacts life insurance purchase intention):** Marginally supported. Hyperbolic discounting showed a negative effect that approached significance.
- **H5 (Age moderates the relationship between Overconfidence and life insurance purchase intention):** Supported. The interaction between Overconfidence and Age was significant, indicating that the negative impact of overconfidence is weaker among older individuals.
- **H6 (Education moderates the relationship between Overconfidence and life insurance purchase intention):** Supported. The interaction between Overconfidence and Education was significant, indicating that the negative impact of overconfidence is weaker among more educated individuals.

- **H7 (Gender moderates the relationship between Social Norms and life insurance purchase intention):** Supported. The interaction between Social Norms and Gender was significant, suggesting that social norms exert a stronger influence on one gender over the other.
- **H8 (Education moderates the relationship between Hyperbolic Discounting and life insurance purchase intention):** Marginally supported, although hyperbolic discounting's main effect was not strongly significant.

Model Diagnostics

To ensure the robustness of the regression models, several diagnostic tests were conducted:

- **Multicollinearity:** Variance inflation factors (VIFs) for all predictors were below 3, indicating that multicollinearity was not a concern.
- **Homoscedasticity:** The scatterplot of standardized residuals versus predicted values did not reveal any patterns, suggesting homoscedasticity.
- **Normality of Residuals:** The histogram and P-P plot of standardized residuals showed that the residuals were approximately normally distributed.

This research shows that overconfidence, loss aversion, and social norms strongly impact life insurance purchasing intentions. Demographic factors including age, gender, and education reduce these impacts. The large interaction effects emphasize the relevance of individual variations in financial decision-making, especially for long-term financial products like life insurance.

The results propose an interactive technique to explore how behavioural and demographic characteristics affect life insurance purchasing.

6. DISCUSSION

This study examined how behavioural biases—Overconfidence, Loss Aversion, Social Norms, and Hyperbolic Discounting—shape life insurance purchase intentions and how demographic factors (Age, Gender, Education, Income) moderate these effects. The study focused primarily on respondents from the low-income and unorganized sectors. Hierarchical regression analysis assessed both direct and interaction effects.

Key Findings

Overconfidence: Negatively impacts life insurance purchase intentions ($\beta = -0.317$, $p < .001$), confirming that overconfident individuals underestimate risks and perceive less need for financial protection (Barber & Odean, 2001; Glaser & Weber, 2007). Addressing overconfidence in financial education programs is crucial.

Loss Aversion: Positively influences purchase intentions ($\beta = 0.220$, $p = .003$), aligning with prospect theory (Kahneman & Tversky, 1979). Loss-averse individuals prioritize insurance as a protective measure (Braun & Muermann, 2004; Sydnor, 2010).

Social Norms: Strongly drive life insurance adoption ($\beta = 0.375$, $p < .001$), supporting social influence theory (Cialdini & Trost, 1998). Cultural expectations and peer influence significantly impact purchase decisions (Botzen et al., 2009).

Hyperbolic Discounting: Negatively affects purchase intentions but is only marginally significant ($\beta = -0.136$, $p = .056$). While individuals prioritize short-term rewards over future security (Laibson, 1997; O'Donoghue & Rabin, 1999), financial literacy or personal circumstances may moderate this effect.

5.1.2 Moderating Effects of Demographic Variables

Adding demographic factors to the regression model increased its explanatory power, and numerous significant interaction effects were found. These results emphasise the relevance of individual variability in behavioural biases and financial decision-making.

Overconfidence and Education: The significant interaction between Overconfidence and Education ($\beta=0.072$, $p<.001$) supports Hypothesis 6. Education mitigates Overconfidence detrimental impact on life insurance purchase intention. This suggests that education may help individuals detect and manage their overconfidence, improving financial decisions (Pallier, 2003). Lusardi & Mitchell (2014) found that education lowers financial decision-making cognitive biases. This indicates the need for financial education programs that reduce overconfidence and enhance risk assessments.

Social Norms and Gender: A significant interaction between Social Norms and Gender ($\beta=-0.347$, $p=.010$) supported Hypothesis 7. The negative interaction shows that Social Norms positively affect life insurance purchasing intention for women more than men. Women are more susceptible to social pressures; therefore they may base their choices on social standards (Eagly & Wood, 1999). This research shows gender variations in financial behavior and suggests societal norms may influence women to obtain insurance.

Overconfidence and Age: A strong interaction between Overconfidence and Age (β=0.132, p=.001) supports Hypothesis 5. Positive interaction shows overconfidence's detrimental influence on life insurance purchasing intention diminishes with age. Life experience and risk awareness may assist seniors control overconfidence (Hvide, 2002). Experience and risk awareness may reduce cognitive biases with age (Frederick, 2005). This suggests that older people may need less overconfidence therapy than younger ones, who may benefit from focused education.

Non-Significant Interactions

Educational and Hyperbolic Discounting interaction was poorly supported (H9) but not statistically significant in the final model. This suggests that schooling may reduce hyperbolic discounting's negative impacts, although other factors may be involved and further study is required.

Theoretical and Practical Implications

This study enhances the understanding of how behavioural biases and demographics shape life insurance purchase intentions, contributing to behavioural economics, financial decision-making, and insurance research. The findings have both theoretical and practical relevance for future research, financial education, and policy.

Theoretical Implications

This research confirms that behavioural biases significantly impact financial decisions. Overconfidence reduces life insurance adoption, reinforcing findings that overconfident individuals underestimate risks (Barber & Odean, 2001). Loss aversion's strong positive effect aligns with prospect theory, indicating that individuals prioritize loss prevention, particularly for family financial security (Kahneman & Tversky, 1979).

Social norms emerge as a key driver of insurance uptake, consistent with research on social influence in financial and behavioural decisions (Cialdini & Trost, 1998; Thaler & Sunstein, 2008). These results highlight systematic deviations from rational decision-making, supporting behavioural economics' argument that cognitive biases shape complex financial choices (Thaler, 2016).

Demographic factors moderate these biases, reinforcing calls for decision-making models that integrate individual attributes with cognitive preferences (Peters et al., 2006; Frederick, 2005). This underscores the role of education, age, and gender in shaping financial behavior.

The study also advances financial literacy research, emphasizing its role in mitigating cognitive biases. Beyond knowledge acquisition, financial literacy should include awareness of biases that lead to suboptimal decisions (Lusardi & Mitchell, 2014), informing more effective financial education programs.

Practical Implications

Financial Education and Consumer Protection

This study highlights the need for financial education programs that address demographic-specific cognitive biases. Targeted initiatives can reduce overconfidence among younger, less-educated individuals and improve risk assessment, increasing life insurance adoption which would help improve insurance penetration and coverage in low-income groups. Programs emphasizing long-term planning can mitigate hyperbolic discounting, encouraging informed financial decisions.

Social norms significantly influence insurance uptake, particularly among women. Public awareness campaigns highlighting life insurance's role in family financial stability can leverage this effect, fostering a stronger sense of financial responsibility.

Policy Implications

The strong influence of behavioural biases on insurance decisions suggests a need for enhanced consumer protection. Regulators should mandate transparent disclosures to counter overconfidence and hyperbolic discounting, ensuring consumers accurately assess long-term risks.

Demographic-specific interventions can improve financial literacy. The low-income and unorganized segments which are often neglected need attention in this regard. Awareness programs for older adults should emphasize maintaining adequate coverage, while younger individuals may need more guidance on risk assessment. Given the role of cultural norms in women's insurance decisions, targeted literacy initiatives can promote informed choices aligned with their financial needs.

Implications for the Insurance Industry

Insurers can refine product design, marketing, and engagement strategies by aligning them with behavioural biases and demographics. Marketing should counter overconfidence by stressing life's uncertainties, appealing to younger, overconfident consumers. Loss aversion can be leveraged by emphasizing financial risks of not having insurance.

Social norms play a key role, especially for women. Marketing that underscores family responsibility and financial security can enhance insurance adoption. Collaborations with community organizations can further reinforce life insurance's societal value.

Product Innovation and Customer Engagement

To counteract hyperbolic discounting, insurers should offer products with immediate benefits or hybrid plans combining savings and protection. Digital tools, such as financial simulations and personalized risk assessments, can help consumers recognize their insurance needs, reducing biases like overconfidence and loss aversion.

Flexible, modular policies catering to changing financial and life circumstances can address uncertainty, appealing to consumers hesitant to commit due to overconfidence. Continuous engagement—such as policy reminders, performance reports, and personalized coverage recommendations—can enhance retention and long-term financial security.

Leveraging social proof through testimonials and success stories may further drive adoption, particularly among women, whose decisions are influenced by relational and societal values.

Implications for Future Research and Development

This study informs both academic research and industry practice by highlighting the role of behavioural biases and demographics in life insurance decisions. Future studies should explore psychological biases in insurance choices, improving predictive models and tailoring financial products to diverse consumer needs.

Broader Societal Implications

Understanding cognitive biases in insurance adoption can enhance financial stability and reduce economic vulnerability. Many individuals underinsure due to biases rather than financial constraints, emphasizing the need for targeted education, marketing, and policy interventions. Addressing demographic disparities can promote more inclusive financial security policies.

Promoting Financial Inclusion

By identifying at-risk groups—such as lower-income individuals, women, and the elderly—insurers and policymakers can design targeted interventions. Financial literacy initiatives and professional guidance can help mitigate cognitive biases, improving insurance accessibility and adoption.

Public Awareness and Engagement

Community-based campaigns leveraging social norms can increase life insurance uptake. Collaborations with influencers, policymakers, and financial institutions can foster trust and enhance public engagement in financial planning.

Scope for Future Research

Methodological Enhancements

This cross-sectional design limits causal inference. Future research should adopt longitudinal approaches to examine how biases evolve with age, experience, and financial circumstances. Expanding research beyond urban populations in India to diverse cultural and economic settings can provide more generalizable insights.

Psychological and Emotional Factors

Beyond cognitive biases, personality traits and emotions significantly influence financial decisions. Future studies should examine how traits like conscientiousness and emotional stability impact insurance choices (Perry & Morris, 2005). Exploring the role of emotions—such as anxiety, fear, and optimism—may further clarify insurance behavior.

Impact of Financial Literacy and Technology

Research should evaluate how financial literacy programs mitigate overconfidence and hyperbolic discounting. Experimental studies testing interventions such as seminars, online courses, and personalized coaching can identify the most effective strategies for long-term behavioural change. Additionally, digital tools, AI, and financial planning apps should be studied for their ability to counteract cognitive biases and improve insurance decision-making.

Cultural and Economic Influences

Comparative studies can explore how cultural values and social norms shape insurance adoption across different societies. The impact of economic factors, such as employment status, inflation, and economic downturns, on cognitive biases and financial decisions warrants further investigation.

Addressing Underinsurance

Future research should examine the long-term financial consequences of underinsurance and identify at-risk populations. Understanding the structural and psychological barriers to adequate coverage can inform policy measures that enhance financial resilience and economic stability.

By advancing research in these areas, scholars and industry professionals can develop more effective financial security systems, fostering greater economic well-being across diverse populations.

7. CONCLUSION

This study examined how demographic factors (Age, Gender, Education, Income) interact with behavioural biases (Overconfidence, Loss Aversion, Social Norms, Hyperbolic Discounting) to shape life insurance purchase intentions. It identifies some key factors related to life insurance purchase decisions in the low-income and unorganized groups. The findings highlight cognitive and social influences on financial decision-making, reinforcing behavioural economics' emphasis on cognitive biases in long-term financial planning.

Overconfidence reduces insurance uptake by leading individuals to underestimate risks, while loss aversion and social norms drive adoption, particularly among women. Education, age, and gender moderate these effects, demonstrating that financial decisions result from complex interactions rather than purely rational calculations. Higher education reduces overconfidence, improving risk assessment (Lusardi & Mitchell, 2014), while social norms shape gender-based financial behaviors.

The study challenges the traditional rational decision-making model, supporting the view that psychological traits, moderated by demographics, influence financial choices. Future research should explore how personality, emotions, and biases further impact financial behavior, refining decision-making frameworks to better reflect human diversity

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