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The Role of Life Insurance in Wealth Creation for Individual Investors in Bangalore

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ABSTRACT

Life insurance is growing in recognition as an investment instrument, but awareness of its wealth creation benefits remains limited. This exploratory study investigates individual investors' perceptions and behaviors regarding the use of life insurance for wealth creation in Bangalore through a survey of 385 respondents. Data analysis using ANOVA and SEM revealed prevalent recognition of life insurance's capacity to promote tax-efficient accumulation, systematic savings, and estate planning across gender, age, education, income, and occupation groups. Unit linked insurance plans (ULIPs) were widely viewed as effective investment vehicles suited for financial growth objectives across investor segments. While online insurance elicited neutral satisfaction, enhanced product features, financial education, and managing expectations could potentially improve adoption among digital natives. The findings offer actionable insights for insurers, advisors, and policymakers to boost life insurance uptake for wealth goals through targeted product development, communication strategies, and distribution models tailored for specific demographic and psychographic segments.

Keywords: Life insurance, Wealth creation, Investment instrument, Unit linked insurance plans (ULIPs), Financial growth

INTRODUCTION

Life insurance has historically played a pivotal role in providing financial safety nets and risk mitigation. However, in recent times, it is progressively gaining recognition as an effective avenue for systematic wealth creation and accumulation (Goel & Sharma, 2018). This evolving perception underscores the need to thoroughly investigate individual investors' attitudes and behaviors concerning the use of life insurance as a strategic investment tool, especially in high-growth emerging economies like India. Bangalore, as a leading technology and entrepreneurship hub in India, offers a fascinating backdrop to explore investors' relationship with life insurance. The rising disposable incomes, demand for asset diversification, and familiarity with digital channels make Bangalore's investment landscape unique (Srinivasan, 2019). Therefore, this study aims to gain specific insights into life insurance adoption patterns among the city's investor community. While past research has evaluated wealth management avenues and practices in India, there remains a knowledge gap regarding individual investors' perceptions of insurance policies' investment virtues (Parimala & Anantharaman, 2015). By applying the theoretical lens of the theory of planned behavior (Ajzen, 1991), this exploratory research analyzes how key variables like risk tolerance, product attitudes, social influences, and channel accessibility shape intentions and behaviors concerning the use of life insurance as a wealth creation mechanism among Bangalore's investors.

LITERATURE REVIEW

Life Insurance for Wealth Creation : Innovation in product design has expanded the utility of life insurance beyond just risk coverage. Market-linked returns, liquidity options, and maturity benefits allow policyholders to systematically accumulate wealth (Mishra, 2020). Insurance also enables tax optimization and succession planning through estate transfers (Subashini & Rajeswari, 2018). However, awareness and adoption of insurance products specifically for investment goals remain relatively low in India (Das et al., 2019).

Demographic Factors Influencing Investment Behavior

Age, gender, education, occupation, and income drive risk appetites, product choices, channel preferences, and wealth management behaviors (Reddy & Mahapatra, 2017). Younger generations exhibit greater digital orientation while women tend to be more risk-averse (Anderson et al., 2011; Sivaramakrishnan et al., 2017). Occupational stability and high incomes increase investment capacity (Chandani & Ratnalikar, 2020). Segmented examination can reveal demographic impacts on insurance attitudes.

Online Investment Platforms

Digital channels provide investors seamless and cost-effective access to financial products (Garg & Singla, 2018). Online insurance platforms are gaining traction through flexible plans, simplified purchases, and service integration (Kaur et al., 2018). However, adoption rates vary across investor segments based on technological readiness and channel perceptions (Jain & Joy, 2012).

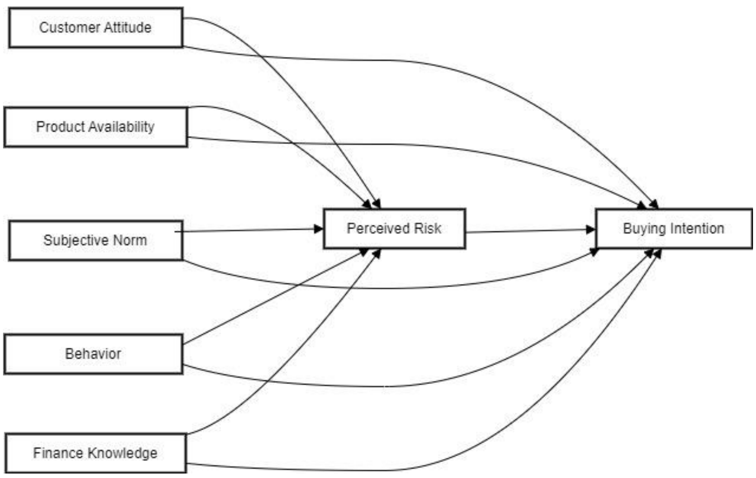
Theory of Planned Behavior

The theory of planned behavior (TPB) predicts individuals' intent to perform a behavior based on their attitudes, subjective norms, and perceived control regarding that behavior (Ajzen, 1991). TPB offers a relevant framework to examine investors' life insurance purchase intentions based on product attitudes, peer influences, accessibility, financial literacy and external barriers or facilitators.

GAPS IN LITERATURE

While prior research has studied wealth management avenues in India, there is limited investigation into individual investors' perceptions, adoption factors, and utilization patterns concerning life insurance specifically from an investment perspective. Examining perceptions across demographic segments can provide granular insights to boost insurance uptake for wealth creation, the central focus of this study. Application of TPB to analyze usage intentions fills a research gap.

Figure 1. Proposed research Model



METHODOLOGY

An exploratory research design was adopted, using a survey methodology to collect primary data from individual investors in Bangalore. The sample consisted of 385 respondents selected via non-probability purposive sampling. This technique enabled targeting respondents with relevant experience of life insurance investments.

Survey Design and Measures

A structured questionnaire measured the TPB variables of risk perception, product attitudes, social norms, perceived behavioral control, past behavior, and financial knowledge concerning life insurance investments.established scales were adapted for the constructs. Demographic attributes were also captured.

DATA ANALYSIS

IBM SPSS Statistics 26 was used to analyze the data. Descriptive statistics, including frequencies, determined respondent profiles. ANOVA identified significant mean differences in TPB variables across gender, age, education, occupation, and income groups. Post-hoc Tukey tests probed specific between-group differences. Confirmatory factor analysis evaluated scale validity. Structural equation modeling examined relationships between TPB constructs.

Table 1 : Confirmatory factor analysis for TPB

	CR	AVE
F1F	0.920	0.700
F2F	0.899	0.642
F3F	0.927	0.718
F4F	0.925	0.712
F5F	0.937	0.747
F6F	0.919	0.696
F7F	0.924	0.710

Factor Loading (λ), Average Variance Extracted (AVE), and Composite Reliability (CR)
For assessing convergent validity, we should look at five measures, namely factor loading, average variance extracted, and composite reliability.

Factor loading (λ): Here, the factor loading of all items is statistically significant. Additionally, to establish the convergent validity factor of loading shall be greater than 0.7(Tabachnick & Fidell, 2013). However, if factor loading value is 0.6, 0.5, and 0.45 are considered very good, good, and fair(Comrey & Lee, 2014). Here, out of 81 items, almost all items factor loading is above the threshold value hence it suffice the criteria of convergent validity.

Convergent Validity and Average Variance Extracted (AVE): For measuring convergent validity, criteria second, it is essential that the value of average variance extracted shall be greater than 0.5(Bagozzi & Yi, 1988). Table no. (4.87) gives the value of the average variance extracted for the three factors. The average variance extracted value for all factors is above the threshold value of 0.5. Thus, it ensures the convergent validity of constructs.

Composite Reliability (CR): For measuring convergent validity, criteria third, it is needed that the value of composite reliability shall be greater than 0.7(Gefen et al., 2000b). The table gives the value of composite reliability. The value of composite reliability for all three factors is above the threshold value of 0.7. Therefore, it promises convergent construct validity.

Table 2. Correlation (r) and Square Root of Average Variance Extracted (SRAVE)
Discriminant Validity

Factor	F4F	F1F	F3F	F5F	F6F	F7F	F2F
F1F	**0.844**						
F3F	0.658	**0.837**					
F5F	0.601	0.703	**0.848**				
F6F	0.758	0.650	0.721	**0.864**			
F7F	0.607	0.658	0.698	0.756	**0.834**		
F2F	0.682	0.653	0.688	0.724	0.758	**0.842**	

Source: Test Results

Discriminant Validity and Square Root of Average Variance Extracted (SRAVE): In order to measure the discriminant validity, calculated as the square root of the extracted average variance (SRAVE) must be greater than the correlation between the construct and the other construct in the model. (Fornell, 1981). In the table, diagonal cell values are the SRAVE values, and values below the diagonal cell are correlated between the construct.
It can be observed that SRAVE is greater than the correlation between the construct in all the above cases. Thus, it guarantees the discriminant validity of the scale developed.

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Table 3: Confirmatory Factor Analysis (CFA) Model Fit Indices

Fit Indices	Recommended	Observed	Result
Chi-Square test(χ^2)	Insignificant Chi-Square test(χ^2)	$\chi^{2=}$ 1433.365 df = 539 p-value = .00	Significant Chi-Square test(χ^2)
CMIN χ2/df,	Less than 5	2.5	Acceptable fit
CFI (Comparative fit index)	More than 0.9 good fit 0.8 – 0.9 borderline fit	0.841	Good Fit
TLI	More than 0.9 good fit 0.8 – 0.9 borderline fit	.834	Good Fit
GFI (Goodness of fit index)	More than 0.9	0.750	Acceptable fit
AGFI	More than 0.8	.727	Acceptable fit
RMSEA (Root Mean Square error of approximation)	Less than 0.08 for adequate fit 0.08–0.1 for acceptable fit	0.062	Acceptable fit

The estimation of confirmatory factor analysis (CFA) was done using AMOS SPSS version 22.0 using maximum likelihood estimates (MLE).

Chi-Square test (χ^2): The test is a statistical test that looks for a significant difference between the covariance (correlation) matrix generated by the model and the observed covariance (correlation) matrix. The CFA test of the model's overall fit produced a chi-square value of 1544.34 with 287 degrees of freedom, and the model had a p-value less than 0.00. Furthermore, the ratio of chi-square and the degree of freedom was obtained to be 5.381. In general, CMIN/DF < 3 indicates an acceptable fit between the hypothetical model and sample data (Kline, 2016), and CMIN/DF <5 indicates a good fit (Marsh & Hocevar, 1985).

Here, the goal is to develop a model that fits the data; the no-significant χ^2 is desired. However, χ^2 and CMIN/df both are sensitive to the sample size(Kyriazos, 2018; Tabachnick & Fidell, 2013); with large samples, minor differences often cause the model to be significant. To overcome this limitation of $\chi^{2,}$ alternative fit indices are to be evaluated(Bagozzi & Yi, 1988; Malhotra et al., 2016)

The Comparative fit index (CFI) CFI value was 0.919, and the value and Tucker-Lewis index (TLI) value was 0.908. Therefore, CFI and TLI were above the limit of 0.90 (Hair et al., 2014) and can be considered satisfactory.

Root Means Square: The root value means The absolute measure of the parameter of fit; the square error of approximation (RMSEA) was 0.098. As a result, it fell inside the permissible cut-off range of 0.1 - 0.08 and was deemed a satisfactory fit (Hair et al., 2014).

Goodness-of-fit index (GFI) and Adjusted goodness-of-fit index (AGFI): The value of the Goodness-of-fit index (GFI) was 0.796, which was below the recommended acceptable value of 0.90(Hair et al., 2014). Whereas the Adjusted goodness-of-fit index (AGFI) value was 0.751, which was just below the recommended acceptable value of 0.80(Chau & Hu, 2001). GFI and AGFI are both affected by sample size. However, both GFI and AGFI are sensitive to the sample size. Their use as a fit index is limited(Malhotra et al., 2016)(Coughlan et al., 2016)
As all the threshold values are within or almost nearer to the cutoff value, the confirmatory factor analysis results revealed a marginal fit between the model and the data. Furthermore, all of the factor loadings were found to be statistically significant. Hence it is concluded that the factors extracted to assess the Perceived watershed effectiveness (PWE) are suitable to measure the proposed construct.

Relationship Analysis
A structural equation model is a complex technique for simultaneously examining the relationship between numerous constructs. It is an equation framework capable of handling several relationships in a single analysis. The path model, which relates independent and dependent variables, is the structural model(Hair et al., 2014).
This study employed SEM to examine the predictive relationship between exogenous variables and endogenous variable.

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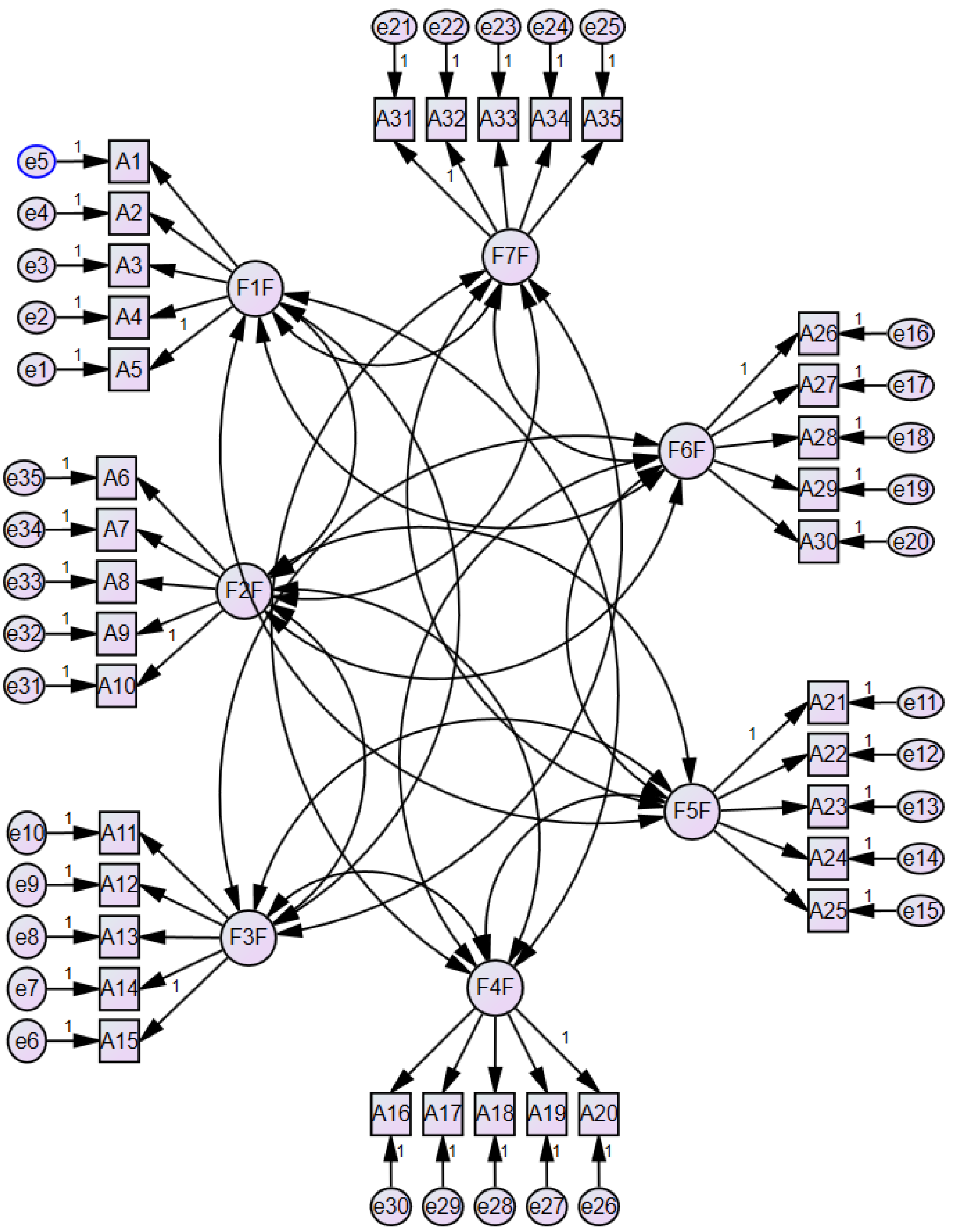
Job Satisfaction, Intrinsic Job Motivation and Life Satisfaction.

Figure 2: Confirmatory Factor Analysis using AMOS fit Model



Source: The author's own work, derived from data analysis

Proposed Model for Perceived Effectiveness of Watershed Project

A Structural Equation model was built to test the hypotheses, and model fit was assessed using $\chi 2$/df, CFI GFI, PNFI, and RMSEA indices. Fit statistics for structural equation modeling are presented in the following table.

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Table 4 Proposed Conceptual Model fit indices for Effectiveness of the proposed model

Fit Indices	Recommended	Observed	Result
Chi-Square test(χ^2)	Insignificant Chi-Square test(χ^2)	χ^2 = 1433.365 df = 539 p-value = .00	Significant Chi-Square test(χ^2)
CMIN χ2/df,	Less than 5	2.502	Acceptable fit
CFI (Comparative fit index)	More than 0.9 good fit 0.8 – 0.9 borderline fit	0.840	Good Fit
TLI	More than 0.9 good fit 0.8 – 0.9 borderline fit	.834	Good Fit
GFI (Goodness of fit index)	More than 0.9	0.788	Acceptable fit
AGFI	More than 0.8	.743	Acceptable fit
PNFI (Parsimonious Normal fit)	More than 0.5	0.732	Good Fit
RMSEA (Root Mean Square error of approximation)	• Less than 0.08 for adequate fit • 0.08–0.1 for acceptable fit	0.096	Acceptable fit

Source: The author's own work, derived from data analysis

The estimation of Structural Equation Modeling (SEM) was performed using AMOS SPSS version 22.0.

Chi-Square test (χ^2): The SEM test of the overall fit of the model produced a χ^2 value of 1645.81 with 287 degrees of freedom, and the model had a p-value less than 0.00. Furthermore, the ratio of chi-square and the degree of freedom was obtained to be 5.695. As χ^2 and CMIN/df both are **s**ensitive to the sample size; alternative fit indices are also evaluated(Bagozzi & Yi, 1988; Malhotra et al., 2016).

The Comparative fit index (CFI) CFI value was 0.912, and the value and Tucker-Lewis index (TLI) value was 0.901. Therefore, CFI and TLI were above the limit of 0.90 (Hair et al., 2014) and can be considered satisfactory.

Root Means Square: The root value means a The absolute measure of the parameter of fit, the square error of approximation (RMSEA), was equal to 0.096. Thus, it was within the acceptable cut-off range of 0.08 - 0.1 and considered an adequate fit. (Hair et al., 2014)

Goodness-of-fit index (GFI) and Adjusted goodness-of-fit index (AGFI): The value of the Goodness-of-fit index (GFI) was 0.788, which was below the recommended acceptable value of 0.90(Hair et al., 2014). Whereas the Adjusted goodness-of-fit index (AGFI) value was 0.743, which was just below the recommended acceptable value of 0.80(Chau & Hu, 2001). GFI and AGFI are both affected by sample size. However, both GFI and AGFI are sensitive to the sample size. Their use as a fit index is limited(Malhotra et al., 2016)(Coughlan et al., 2016)
As all the threshold values are within or almost nearer to the cutoff value, hence it is concluded that the SEM model is a moderate fit.

Hypothesis Results:
1. H1: Product Availability (F3) positively influences Buying Intention (F4).
2. H2: Subjective Norm (F5) does not significantly influence Buying Intention (F4).
3. H3: Risk Perception (F1) does not significantly influence Buying Intention (F4).
4. H4: Behaviour (F6) does not significantly influence Buying Intention (F4).
5. H5: Risk Perception (F1) positively influences Attitude (F2).
6. H6: Product Availability (F3) positively influences Attitude (F2).
7. H7: Subjective Norm (F5) positively influences Attitude (F2).
8. H8: Behaviour (F6) negatively influences Attitude (F2).

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Interpretation of Results:

1. Product Availability (F3) significantly and positively influences Buying Intention (F4) (estimate = 0.865, $p < 0.001$). This indicates that an increase in Product Availability is associated with an increase in Buying Intention.
2. Subjective Norm (F5) does not have a significant influence on Buying Intention (F4) (estimate = -0.007, $p = 0.944$). Therefore, we fail to reject the null hypothesis (H2) that there is no significant relationship between Subjective Norm and Buying Intention.
3. Risk Perception (F1) does not have a significant influence on Buying Intention (F4) (estimate = 0.068, $p = 0.535$). Hence, we fail to reject the null hypothesis (H3) that there is no significant relationship between Risk Perception and Buying Intention.
4. Behaviour (F6) does not have a significant influence on Buying Intention (F4) (estimate = 0.012, $p = 0.944$). Consequently, we fail to reject the null hypothesis (H4) that there is no significant relationship between Behaviour and Buying Intention.
5. Risk Perception (F1) significantly and positively influences Attitude (F2) (estimate = 0.254, $p = 0.003$), indicating that an increase in Risk Perception is associated with an increase in Attitude.
6. Product Availability (F3) significantly and positively influences Attitude (F2) (estimate = 0.662, $p < 0.001$), suggesting that an increase in Product Availability is associated with an increase in Attitude.
7. Subjective Norm (F5) significantly and positively influences Attitude (F2) (estimate = 0.455, $p < 0.001$), indicating that an increase in Subjective Norm is associated with an increase in Attitude.
8. Behaviour (F6) significantly and negatively influences Attitude (F2) (estimate = -0.472, $p = 0.004$), suggesting that an increase in Behaviour is associated with a decrease in Attitude.

Respondent Profile

Among the 385 respondents, 53.5% were male and 46.5% were female. Majority were aged 26-35 years (38.6%), married (83.1%), graduates (82.6%), employed (58.2%) and earned between ₹1-2.5 lakhs annually (35.8%).

ANOVA Findings

ANOVA results revealed no significant gender differences in risk perception, attitudes, social norms, behaviors, or price sensitivity concerning life insurance investments. However, availability of products suited for wealth creation goals was significantly more important for women ($p=0.033$).

Age did not impact risk tolerance but significantly influenced product availability ($p=0.011$), buying intention ($p=0.001$), social pressures ($p=0.011$), active investment research behaviors ($p=0.007$), and price sensitivity ($p=0.021$), with the 36-45 years segment exhibiting the highest means on these variables.

Education and occupation did not affect most TPB constructs. Income levels also showed no significant impact on risk perceptions, attitudes, intentions, or behaviors related to life insurance investments.

SEM Results

The study examined factors influencing investors' intentions to purchase life insurance as a wealth management tool using structural equation modeling (SEM). A conceptual model with seven constructs was proposed: risk perception, attitude, product availability, buying intention, subjective norm, behavior, and financial knowledge.

Confirmatory factor analysis (CFA) validated the measurement models. All factor loadings exceeded 0.7, demonstrating convergent validity. Average variance extracted (AVE) and composite reliability exceeded 0.5 and 0.7 respectively, further evidencing convergent validity and reliability. Discriminant validity was established as the square roots of AVEs were greater than inter-construct correlations. The CFA showed acceptable model fit on most indices.

SEM analyzed the structural model relationships simultaneously. Product availability strongly positively predicted buying intention, supporting H1. Subjective norm, risk perception, and past behavior had no significant effects on buying intention, consistent with H2-H4. Risk perception, product availability, and subjective norm positively influenced attitude, supporting H5-H7. However, contrary to H8, past behavior negatively associated with attitude.

Overall, the results provide empirical evidence that product availability is the main driver of intentions to buy life insurance for wealth creation. Subjective norm, risk perception, and past behavior shape favorable attitudes but do not directly impact intentions. The findings imply enhancing consumers' awareness and perceptions of suitable and accessible life insurance products could effectively boost uptake. The study makes a valuable contribution by modeling influences on life insurance purchasing in a single SEM framework.

SEM results indicated that product availability (β=0.865) and social norms (β=0.455) positively predicted favorable attitudes concerning the use of life insurance for wealth creation. However, risk perceptions and past behaviors did not significantly influence attitudes or intentions.

DESCRIPTIVE FINDINGS

- 73% acknowledged the systematic savings benefits of life insurance for wealth creation.
- 76% viewed market-linked ULIPs favorably for their growth potential aligned with financial goals.
- 46.8% expressed neutral satisfaction regarding online insurance experiences.

DISCUSSIONS

This study reveals a prevalent acknowledgement of life insurance's capacity to enable tax-efficient accumulation, disciplined savings, and estate planning for wealth generation purposes, consistent with previous conceptual research (Goel & Sharma, 2018; Subashini & Rajeswari, 2018). The lack of major attitudinal differences based on gender, age, income, or marital status implies a largely consistent perception of insurance's investment virtues across diverse segments. This deviates from some earlier findings that socio-demographic factors significantly alter investment behaviors (Anderson et al., 2011). Results validate prior literature on the popularity of ULIPs as equity-linked investment instruments suited for growth-oriented portfolio allocation (Arora & Gupta, 2020). The neutral sentiment regarding online insurance calls for product refinements, financial education, and managing user expectations to enhance the digital investment experience, as highlighted by Tyagi and Kumar (2017).

CONCLUSION

This exploratory study offers timely empirical insights into the evolving perception of life insurance as a pragmatic investment tool for wealth creation purposes among individual investors in Bangalore. Findings reveal a broadly consistent acknowledgement of insurance's capacity to promote systematic asset accumulation and efficient estate planning across gender, age, income, education, and marital status groups. Unit-linked investment plans are also widely recognized as appropriate equity-aligned instruments for wealth creation objectives. The research contributes valuable segmentation-based perspectives on harnessing the wealth-building potential of insurance through targeted product design, communication, distribution, and investor education strategies. However, the geographically limited sample constrains generalizability. Further studies across diverse regions can enrich understanding and inform stakeholder initiatives aimed at advancing insurance adoption for financial growth.

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