Journal of Informatics Education and Research
ISSN: 1526-4726
Vol 5 Issue 1 (2025)

A Study of the Role of Loss Aversion Bias in Loss Aversion Effort in Buying Life Insurance Product

Mr. Hunasing Engti[1],
[1]Dept. Of Commerce,
Assam University Diphu Campus, Diphu, Karbi Anglong, Assam
Prof. Amalesh Bhowal[2]
Dept. Of Commerce,
Assam University Diphu Campus, Diphu, Karbi Anglong, Assam,

ABSTRACT
This research framework provides a small sample-based comprehensive approach to studying the impact of loss aversion bias on life insurance product selection using neural network analysis and bootstrapping. By focusing exclusively on loss aversion as a latent variable, along with a few selective demographic profiles, the study provided deeper insights into the cognitive processes that drive consumer behaviour in the form of the degree of loss aversion bias along with demographic variables that impact buying insurance policies in the life insurance market. The findings are valuable for academic research in behavioural finance and practical applications in the insurance industry.

Keywords: Loss aversion bias, life insurance product, neural network, bootstrapping

1. Introduction

Loss aversion bias is a key concept in behavioural economics as behavioural finance. It significantly affects consumer decision-making, particularly in contexts involving risk and uncertainty, such as life insurance.

2. Literature review

To ensure a systematic insight into the existing literature on loss aversion bias in life insurance decisions, relevant studies were sourced from academic databases such as Google Scholar. A total of 77 papers were selected based on the citation score of the documents that popped up when the Keywords like "loss aversion," "life insurance," "decision-making "and" behavioural finance" neural network analysis¸ Bootstrapping¸ studied for detailed review.

Loss aversion reference suggests that losses are perceived as more significant than gains of the same magnitude. This principle is crucial in understanding financial decisions, including life insurance, where the potential for future losses (e.g., loss of income or financial stability) drives purchasing behaviour. Loss aversion, a concept from behavioural economics, plays a critical role in life insurance decisions, as individuals tend to avoid losses more strongly than they pursue equivalent gains. This bias often influences consumers to purchase life insurance as a protective measure against potential financial losses rather than for the potential benefits.

The bias of loss aversion directly impacts how individuals perceive and react to life insurance. People tend to overvalue potential losses compared to gains, influencing their decisions to purchase insurance as a safeguard. This bias makes them more likely to opt for insurance products that provide guaranteed returns or protection, thereby reinforcing the industry's focus on loss-prevention features rather than the potential benefits of investment-linked policies.

The choice of buying life insurance is beset with intricate dimensions. [1] Life insurance can serve as an investment vehicle, combining protection with savings or investment components, offering returns and tax benefits. Hence¸ Life Insurance has the character of an Investment

[2] Life insurance is often seen as a tool for loss aversion, minimizing potential future financial loss by providing payouts upon adverse events. This is pertinent.

[3] Life insurance is also considered a loss prevention tool, providing financial support to dependents and covering potential risks.

Thaler suggests that consumers segregate insurance expenses into a "loss" account, making them particularly sensitive to potential out-of-pocket costs when selecting insurance. This suggests insurance is more of Loss aversion than the other dimensions.

Demographic factors influence decision-making regarding the choice of going for a life insurance policy or not going for that. These include factors like Age, gender, and family structure as moderators of loss aversion Income Level- Economic, demographic, and institutional determinants of life insurance consumption across countries¸ Marital Status.

2.1 The research gap that emanates from the above survey of the literature is whether demographic variables determine alone choice of insurance product buying alone or whether the degree of Loss Aversion bias determines that or they collectively influence the choice of insurance product buying ¸and¸ if collectively¸ then moot question is which of these are important to what extent. Normally neural network analysis is carried out with a large number of samples ¸but this is possible for a small number of samples with appropriate scientific methodology. Whether small-sized sample-based studies reveal similar findings or not- this was another motivation for the present study.

2.2 Significance of the study: Understanding the underlying cognitive biases, consumer perceptions, and policy implications can provide valuable insights into how consumers make insurance decisions and how insurers and regulators can better design and present life insurance products to align with consumer needs and preferences.

3. Methodology followed

3.1 Research Objectives

1. To identify the degree to which loss aversion bias influences the selection of life insurance policies.
2. To predict the likelihood of policy selection or non-selection based on the level of loss aversion bias.
3. To evaluate the predictive capability of a neural network model in understanding the non-linear relationships between loss aversion bias and life insurance product selection where profiles of the decision makers are acting as mediating variables.
4. To validate the model predictions using bootstrapping techniques to ensure robustness and generalizability.
5. Whether small-sized sample-based studies reveal similar findings or not compared to the large sample-based studies

3.2 Scope of the study: The study focused exclusively on how loss aversion bias—considered as a latent variable—affects the decision-making process for purchasing or not purchasing life insurance products mediated by the personal profile of the decision maker regarding the decision to buy a policy or not.

3.3 Sample and Data Collection Method

A purposive sampling was done and a questionnaire was served to 50 respondents. However complete responses were received from 41 respondents selected through purposive sampling to represent different demographic and socioeconomic backgrounds – like age, gender, total annual income (including all sources), marital status¸ family member's number¸ years of work experience. Participants were also subjected to answering 10 items in the scale to measure the degree of Loss aversion bias in a five-point scale. Participants' choices regarding their past buying of Life Insurance policies were elicited as binary outcomes were categorized as 1 for selection and 0 for non-selection.

3.4 Analysis design

The latent Variable considered for the study was Loss Aversion Bias since it cannot be directly observed but can be inferred from respondents' answers to specific questions. A series of 10 statements were identified and respondents were asked to respond on a 5-point scale to gauge their level of loss aversion**.** This latent variable was also used as an input variable**.**

10 statements were used to identify the underlying variable Loss Aversion bias (in this case, the 10 items in the current scale). Calculated the reliability score (Cronbach's alpha) for the scale was calculated. The reliability score indicates the consistency of the items in measuring a latent construct. Higher reliability (usually above 0.7) suggests that the scale is reliable.

Neural network Analysis is particularly useful in this context due to its ability to model complex, non-linear relationships that traditional regression methods may not capture. In the present study, the non-linear relationship was assumed. A neural network model was developed to analyze the relationship between the latent variable (loss aversion bias) and demographic variables as input variables and a neural network model was created with input nodes for demographic factors and loss aversion bias score, hidden layers for capturing non-linear interactions, and an output node for predicting the selection of life insurance policies.

Outcome Variable was Life Insurance Product Selection. The outcome variable, life insurance product selection, is defined as a binary variable: 1 for selecting a policy and 0 for not selecting a policy. Input variables are Age [variable2]¸ Marital status [variable3]¸ Number of dependent(s) [variable4]¸Years of work Experience (number of years) [variable5]¸Approximate total annual income (including all sources) [variable6]¸Please indicate whether you currently have any life insurance policies [variable7]¸loss aversion score [variable 22].

Here multilayer perception was used. Accordingly, data partitioning was done training: test = 70:30. Automatic architecture selection with a minimum number of units in hidden layer =1, and a maximum number of units in hidden layer=50 was done, Type of training used – batch training, missing values in covariates and scale-dependent variables were excluded, a number of epoch (repetition) was set automatic.

The Analysis of Case Processing Summary¸ Network Information¸ Network Diagram¸ Model Summary¸ Classification¸ Parameter Estimates¸ Area Under the ROC [Receiver Operating character] Curve [both graph and score]¸ Independent Variable Importance including Normalized Importance scores and graph as generated by SPSS16 was done to assess the model performance.

Bootstrapping techniques were used to validate the neural network model's predictions. Bootstrapping involves repeatedly sampling from the same dataset with replacement and estimating the model to assess the stability and reliability of the predictions. This process helps in understanding the variability and confidence intervals of the model's output, providing a robust check against overfitting. This provided a measure of internal consistency.

Bootstrapping was used to generate multiple resampled datasets and re-run the neural network model additional time to check for the consistency of results. Analysis of the distribution of predictions across the bootstrapped samples is used to estimate the coefficient of variation and assess prediction stability. This indicated the Generalisation capacity of the model.

Bootstrapping is a robust statistical technique that can help in estimating the stability and generalizability of a reliability score (such as Cronbach's alpha) by generating multiple resamples from the original dataset.

By creating multiple bootstrapped subsamples, each consisting of 80% of the original sample size (which is approximately 33 respondents for each subsample) for 11 times neural network analysis. It was possible to generalize the reliability score calculated by scale reliability measure using bootstrapped subsamples. Similarly for Model Summary¸ Classification¸ Area Under the ROC [Receiver Operating character] Curve [score]¸ Independent Variable Importance including Normalized Importance scores as generated by SPSS16 generated by neural network analysis done for the same data set and then estimating the coefficient of variation of these 10 sets provides the estimate of the internal consistency of the model generated by neural network model.

Generalizing the Reliability Score required the reliability scores obtained from the 11 bootstrapped subsamples. These were used to get the mean, standard deviation and coefficient of variation to get a generalized overall reliability estimate. Generalization was done for Similarly for Model Summary¸ Classification¸ Area Under the ROC [Receiver Operating character] Curve [score]¸ Independent Variable Importance including Normalized Importance scores as generated by SPSS16 generated by neural network analysis done for on the different data set generated by and then estimating the coefficient of variation of these 10 data sets provides the estimate of the internal consistency of the model generated by neural network model. Given that the original sample size is relatively small (41 respondents), bootstrapping is particularly valuable because it helps mitigate the limitations of small sample sizes by generating multiple datasets for analysis. Ultimately the model was run.

4. Results

Sample Profile

Table I: Gender Profile of samples

	Frequency	Percent
Female	22	53.65854
Male	19	46.34146
Total	41	100

Source: compiled from survey data

Table II: Age profile of samples

Age	Frequency	Percent
26	2	4.878049
27	1	2.439024
29	1	2.439024
30	1	2.439024
31	5	12.19512
32	7	17.07317
33	3	7.317073
34	5	12.19512
35	2	4.878049
36	2	4.878049
37	2	4.878049
38	1	2.439024
39	2	4.878049
40	1	2.439024
41	2	4.878049
42	2	4.878049
45	1	2.439024
48	1	2.439024
Total	41	100

Source: compiled from survey data

Table III: Marital Status of samples

marital status	Frequency	Percent
Divorce	1	2.439024
Married	26	63.41463
Single	13	31.70732
Widowed	1	2.439024
Total	41	100

Source: Compiled from survey data

Table IV: Family members size

	Frequency	Percent
0	2	4.878049
1	10	24.39024
2	6	14.63415
3	7	17.07317
4	7	17.07317
5	7	17.07317
6	1	2.439024
9	1	2.439024
Total	41	100

Source: compiled from survey data

Table V: Years of works experience

	Frequency	Percent
2	7	17.07317
3	8	19.5122
4	1	2.439024
5	2	4.878049
6	3	7.317073
7	3	7.317073
8	4	9.756098
9	1	2.439024
10	3	7.317073
11	1	2.439024
12	3	7.317073

15	1	2.439024
17	1	2.439024
18	1	2.439024
21	1	2.439024
23	1	2.439024
Total	41	100

Source: compiled from survey data

Table VI: Approximate total annual income
(including all sources)

	Frequency	Percent
Less than 400000	18	43.90244
400001 - 600000	10	24.39024
600001 - 800000	7	14.63414
800001 - 1000000	3	7.317073
1000001 - 120000	3	7.317073
1200001 and Ab	1	2.439024
Total	41	100

Source: compiled from survey data

Table VII: whether respondents currently have any life insurance policies

	Frequency	Percent
No	18	43.90244
Yes	23	56.09756
Total	41	100

Source: compiled from survey data

The sample profile is the testimony of the confluence of various dimensions which are self-explanatory.

4.1 Model Testing and Prediction:

Table VIII: Indicators used to measure the degree/level of / score of Loss aversion bias

variable 12	I prefer low-risk investments with guaranteed returns over high-risk high-reward options
variable 13	I am more comfortable investing in life insurance schemes that have a fixed sum assured rather than those linked to market performance
variable 14	I would rather avoid investing in life insurance schemes if there is a possibility of losing my principal amount
variable 15	I tend to choose life insurance plans that offer stability even if the returns are lower
variable 16	I feel anxious about investing in life insurance schemes that involve any level of uncertainty or risk
variable 17	I believe it is better to be safe than sorry so I avoid life insurance plans with variable returns
variable 18	I prefer life insurance products that guarantee a payout even if it means paying higher premiums
variable 19	The fear of potential losses makes me hesitant to invest in life insurance schemes with fluctuating benefits
variable 20	I prioritize security over potential high returns when choosing life insurance plans
variable 21	I would avoid investing in life insurance unless I can be sure of receiving back at least my premium payments.

Source: compiled from a survey of literature

A reliability score of 0.765 [Cronbach alfa] leaves behind the evidence that indicators are competent enough to measure the level of loss aversion bias in the choice of buying or not buying an insurance product.

4.2 Case processing summary

Table IX: Case Processing Summary of the model

		N
Sample	Training	21
	Testing	17
Valid		38
Excluded		3
Total		41

Source: compiled from survey data

The data set used for neural network analysis consisted of 41 samples out of these only 3 items were excluded because of missing values as well as data consistency. The exclusion made the model performance a robust one. This ensures that the model is adequately trained and tested on separate data sets.

Table X: Network Information of the model

Input Layer	Factors	1	Gender	
		2	Marital status	
		3	Approximate total annual income (including all sources)	
	Covariates	1	Age	
		2	Number of dependent(s)	
		3	Years of Experience (number of years)	
		4	loss aversion score	
	Number of Units [a]			12
	Rescaling Method for Covariates		Standardized	
Hidden Layer(s)	Number of Hidden Layers			1
	Number of Units in Hidden Layer 1a			3
	Activation Function		Hyperbolic tangent	
Output Layer	Dependent Variables	1	Please indicate whether you currently have any life insurance policies	
	Number of Units			2
	Activation Function		Softmax	
	Error Function		Cross-entropy	

a. Excluding the bias unit

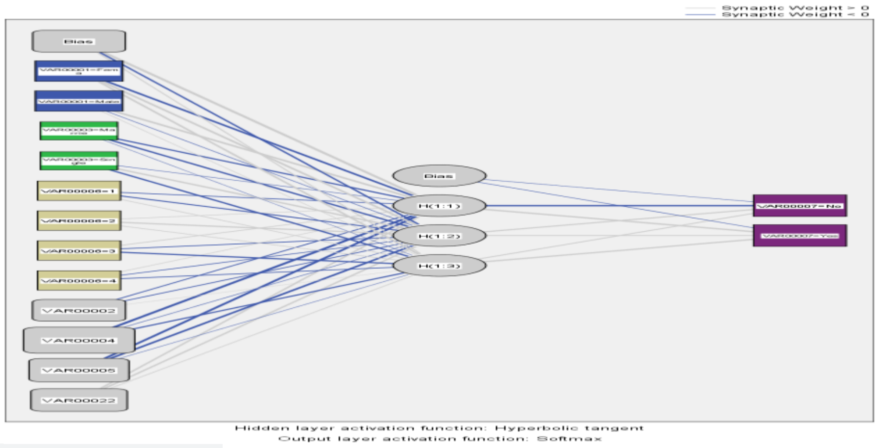
Source: compiled from survey data

From the above, it can be discerned that the model can effectively learn from the data and assess how the choice of policy is determined by demographic variables and level of loss aversion bias.

Parameters of estimates: This includes the weights and biases associated with each connection between neurons and the network. These parameters are adjusted during training to minimize the error between the predicted and actual values. Thus, it guides the model to capture better the underlying patterns in the data. This optimization process fine-tunes these parameters to improve the accuracy and effectiveness of the model's prediction.

4.3 Weights and biases

These parameters try to adjust during training to minimize prediction error. Weights are the indicators of the strength of connections between neurons, while biases shift the activation function to help the network learn complex patterns.



Source: compiled from survey data

This diagram is a simple feed-forward neural network with one hidden layer. The input layer consists of 6 variables followed by a hidden layer of 3 neurons and output layers with two possible outcomes. The synaptic weights between layers are either positive [blue lines] or negative [grey lines]. The activation function used is the sigmoid function for the hidden layer and SoftMax for the output layer.

Parameter Estimates

Predictor		Predicted				
		H(1:1)	H(1:2)	H(1:3)	[VAR00007 =No]	[VAR00007 =Yes]
Input Layer	(Bias)	0.634	-0.34	0.23		
	[VAR00001=Female]		-0.452	0.404		
	[VAR00001=Male]	0.515	-0.094	0.0745		
	[VAR00003=Married]	-0.414	-0.434	-0.026		
	[VAR00003=Single]	-0.129	0.465	-0.431		
	[VAR00006=1]	-0.338	-0.400	0.284		
	[VAR00006=2]	0.245	0.474	0.294		
	[VAR00006=3]	0.329	-0.344	-0.467		
	[VAR00006=4]	0.197	-0.304	-0.341		
	VAR00002	-0.312	-0.317	0.030		
	VAR00004	-0.646	-0.108	-0.409		
	VAR00005	-0.465	-0.461	-0.045		
	VAR00022	0.357	0.385	0.192		
Hidden Layer 1	(Bias)				-0.122	-0.190
	H(1:1)				-0.985	0.821
	H(1:2)				0.447	0.378
	H(1:3)				0.351	0.479

Source: compiled from survey data

The numerical values associated with the network diagram are reflected in the table. The weights between the hidden layer and output layers represent the influence of each hidden neuron on the predicted outcome.

4.4 Model accuracy

Table XI: Model Summary score of the model

Training	Cross Entropy Error	10.70895999
	Percent Incorrect Predictions	23.80952381
	Stopping Rule Used	1 consecutive step(s) with no decrease in error [a]
	Training Time	0:00:00
Testing	Cross Entropy Error	10.35317238

Journal of Informatics Education and Research
ISSN: 1526-4726
Vol 5 Issue 1 (2025)

	Percent Incorrect Predictions	29.41176471
Dependent Variable: Please indicate whether you currently have any life insurance policies		
a. Error computations are based on the testing sample.		

Source: compiled from survey data

The key matrix here includes a percentage of incorrect prediction and cross-entropy error. These metrices provide insight into how well the model can classify the dependent variable across both training and testing data set. From the data above it can be discerned that the model is calibrated and performs effectively in predicting the dependent variable related to the decision to purchase of insurance product.

4.5 Confusion matrix:

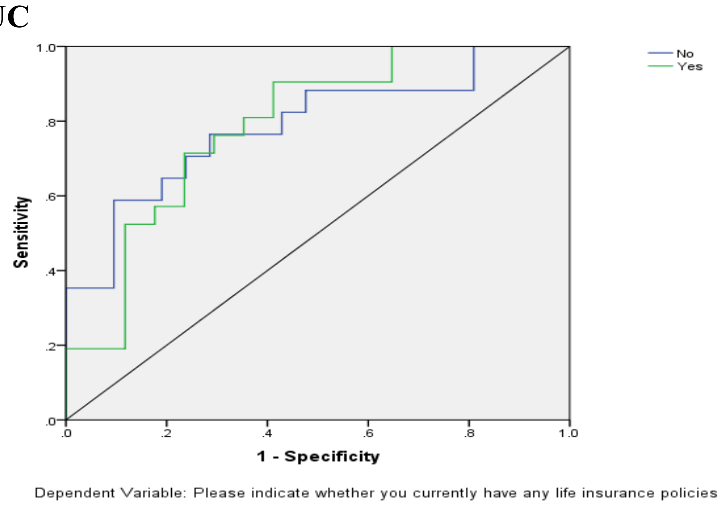
Table XII: Classification scores

Sample	Observed	Predicted		
				Percent Correct
Training	No	7	3	70
	Yes	2	9	81.81818
	Overall Percent	42.85714	57.14286	76.19048
Testing	No	5	2	71.42857
	Yes	3	7	70
	Overall Percent	47.05882	52.94118	70.58824
Dependent Variable: Please indicate whether you currently have any life insurance policies				

Source: compiled from survey data

It provides a detailed breakdown of the model's classification performance¸comparing observed outcomes with predicted ones. This signifies the model's classification power. This hints at the model's precision and recall¸contributing to the overall evaluation of its accuracy. Overall accuracy in the training data set is 77% and in the test set is 71%. This is evidence that the model is the best-performing classification function and highly effective in predicting the choice for buying a life insurance product.

4.6 ROC and AUC



Source: compiled using survey data

Table XIII: Area Under the Curve of the model

		Area
Please indicate whether you currently have any life insurance policies	No	0.787115
	Yes	0.787115

Source: compiled from survey data

These are the key metrics used to evaluate the performance of a binary classifier. The ROC demonstrates the tradeoff between sensitivity and specificity. Thus, indicates the model's classification power. Since the score is 0.78711¸ it is evident that the model can very well classify the decision makers who would go for life insurance products or not.

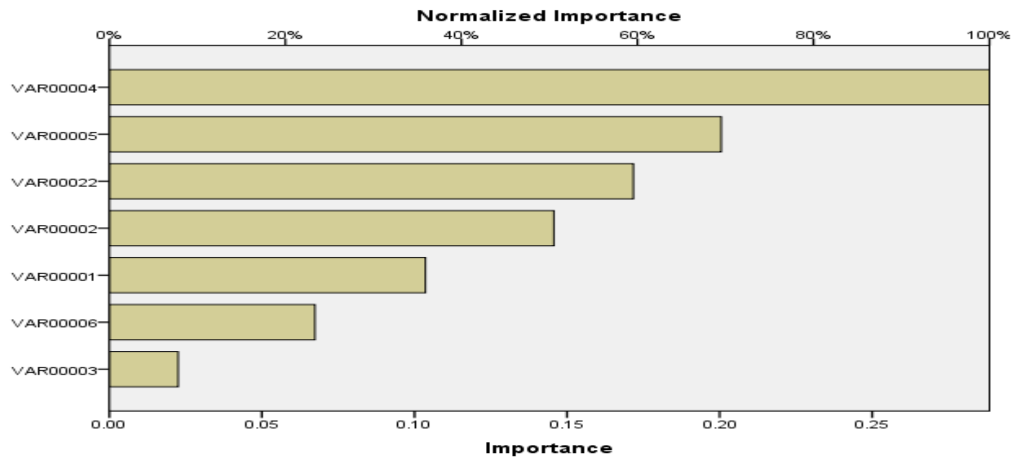
Journal of Informatics Education and Research
ISSN: 1526-4726
Vol 5 Issue 1 (2025)

4.7 Significance predictor:

Table XIV: Independent Variable Importance of the model

	Importance	Normalized Importance
Gender	0.103625	35.92528
Marital status	0.022557	7.820249
Approximate total annual income (including all sources)	0.067397	23.36545
Age	0.145675	50.50349
Number of dependent(s)	0.288446	100
Years of Experience (number of years)	0.200556	69.52963
loss aversion score	0.171744	59.54101

Source Compiled from survey data using spss 16



Source: compiled from Survey data

Number of dependents [.28], years of work experience [.20] and loss aversion score [.17] are the most impactful variables. Interestingly approximate total income is less impactful than loss aversion bias supporting the claim of prospect theory. Interestingly gender and Marital status are less impactful variables in the choice of life insurance product buying.

Given the data set and the selected methodology, from the above tables and diagrams generated by Neural network analysis, it is discernible that the model in question is an optimum fit.

4.8 Assessment of internal consistency

Table XV: Model Summary scores for Internal consistency

	Training		Testing	
	Cross Entropy Error	Percent Incorrect Predictions	Cross Entropy Error	Percent Incorrect Predictions
run 01	11.1887	21.875	4.942313	22.22222
run 02	12.10019	20.68966	3.669539	9.090909
run 03	15.53252	23.07692	8.96971	46.15385
run 04	14.03197	25	9.634765	29.41176
run 05	16.66868	24.13793	6.70758	33.33333
run 06	12.03634	14.81481	8.778451	28.57143
run 07	11.52246	20	2.955141	10
run 08	15.54817	22.22222	8.722365	28.57143
run 09	11.70149	17.85714	6.496082	38.46154
run 10	15.86914	26.92308	7.297122	21.42857
average	13.61997	21.65968	6.817307	26.7245
SD	1.923721	3.196321	2.104801	10.49653
cv	14.12427	14.75701	30.87438	39.27679

Source: compiled from survey data

Table XVI: Classification score regarding Interna consistency						
Sample	Training			Testing		
	No	Yes	Overall Percent	No	Yes	Overall Percent
Percent Correct	69.23077	84.21053	78.125	100	50	77.77778
Percent Correct	69.23077	87.5	79.31034	75	100	90.90909
Percent Correct	70	81.25	76.92308	25	100	53.84615
Percent Correct	83.33333	66.66667	75	66.66667	72.72727	70.58824
Percent Correct	76.92308	75	75.86207	80	57.14286	66.66667
Percent Correct	80	88.23529	85.18519	50	100	71.42857
Percent Correct	57.14286	100	80	75	100	90
Percent Correct	60	88.23529	77.77778	62.5	83.33333	71.42857
Percent Correct	69.23077	93.33333	82.14286	60	62.5	61.53846
Percent Correct	72.72727	73.33333	73.07692	85.71429	71.42857	78.57143
average	70.78188	83.77644	78.34032	67.9881	79.7132	73.2755
sD	7.349166	9.012949	3.196321	18.70543	17.74913	10.49653
cv	10.38283	10.75833	4.080046	27.5128	22.26624	14.32474

Source: Compiled from survey data

Table VII: Area Under the Curve score – internal consistency		
	No	Yes
sample 1	0.896135	0.896135
sample 2	0.902813	0.902813
sample 3	0.698413	0.698413
sample 4	0.777778	0.777778
sample 5	0.785024	0.785024
sample 6	0.81401	0.81401
sample 7	0.906566	0.906566
sample 8	0.775362	0.775362
sample 9	0.850242	0.850242
sample 10	0.739899	0.739899
average	0.814624	0.814624
sD	0.065372	0.065372
Cv	8.024752	8.024752

Source: compiled from survey Data

Table XVIII: Independent Variable Importance Score for Internal Consistency							
	Gender	Marital status	Approximate total annual income (including all sources)	Age	Number of dependent(s)	Years of Experience (number of years)	loss aversion score
sample 01	0.049191	0.076256	0.242266	0.240902	0.154644	0.135147	0.101594

sample 02	0.069356	0.099359	0.13444	0.135538	0.323475	0.11708	0.12075
sample 03	0.041485	0.025667	0.120188	0.245109	0.047461	0.227964	0.292125
sample 04	0.082166	0.069021	0.109264	0.254885	0.235441	0.12992	0.119304
sample 05	0.013626	0.106264	0.127732	0.227133	0.415587	0.104797	0.004862
sample 06	0.052205	0.078856	0.198694	0.228975	0.188058	0.159496	0.093716
sample 07	0.068073	0.069046	0.082382	0.311758	0.186085	0.165864	0.116793
sample 08	0.076129	0.149517	0.104371	0.160331	0.346999	0.111111	0.051542
sample 09	0.050037	0.081332	0.117079	0.338681	0.220111	0.088086	0.104675
sample 10	0.022976	0.021782	0.126504	0.232383	0.339739	0.033867	0.222749
average	0.052525	0.07771	0.136292	0.237569	0.24576	0.127333	0.122811
SD	0.020195	0.033634	0.043255	0.054507	0.099655	0.046579	0.073438
cv	38.4495	43.2817	31.73727	22.94356	40.54965	36.58062	59.79769

Source: compiled from survey data

Table XIX: Independent Variable Importance Normalized Importance score for internal consistency

	Gender	Marital status	Approximate total annual income (including all sources)	Age	Number of dependent(s)	Years of Experience (number of years)	loss aversion score
sample 1	20.30459	31.47599	100	99.43709	63.83237	55.78431	41.93472
sample 2	21.4409	30.71617	41.56127	41.90072	100	36.19457	37.32908
sample 3	14.20126	8.786206	41.14264	83.90537	16.24674	78.03652	100
sample 4	32.23669	27.07933	42.8679	100	92.37154	50.97201	46.80694
sample 5	3.278637	25.56964	30.73538	54.65345	100	25.2165	1.169811
sample 6	22.79942	34.43851	86.77528	100	82.13044	69.65626	40.92834
sample 7	21.83527	22.1474	26.42494	100	59.68887	53.20281	37.46269
sample 8	21.93937	43.08865	30.07814	46.20487	100	32.02042	14.85367
sample 9	14.77415	24.01432	34.5692	100	64.9907	26.00846	30.90655
sample 10	6.76278	6.411398	37.23572	68.40045	100	9.968612	65.56466
average	17.95731	25.37276	47.13905	79.4502	77.92607	43.70605	41.69565
SD	7.633112	10.05299	22.75548	22.07568	24.63972	19.36989	24.33128
cv	42.507	39.62119	48.27309	27.78556	31.61936	44.31857	58.35449

Source: compiled from the survey data

For assessing internal consistency¸ same model was applied 10 repeated times on the same 41 samples. From the above mean, standard deviations and coefficient of variation¸ derived based 10 times neural network analysis on the same set of data revealed that there exists internal consistency of the model applied.

5. Results of Generalization based on bootstraps sampled

Table XX: Generalization of Reliability Score

Journal of Informatics Education and Research
ISSN: 1526-4726
Vol 5 Issue 1 (2025)

sample number	Cronbach's Alpha
1	0.77409
2	0.76587
3	0.82055
4	0.78534
5	0.79411
6	0.72294
7	0.76148
8	0.80707
9	0.71146
10	0.77455
11	0.78534
N	11
Minimum	0.71146
Maximum	0.82055
Mean	0.77298
Std. Error	0.00984
Std. Deviation	0.03264
CV	4.22246
Variability	Low

Source: Compiled from survey Data

Table XXI: Generalization of Model Summary Scores

sample number	Cross Entropy Error	Percent Incorrect Predictions	Cross Entropy Error	Percent Incorrect Predictions
1	12.14472	28	3.138564	15.8
2	9.872748	17.3913	3.757094	25
3	12.18943	42.10526	6.237615	30
4	10.34221	13.04348	2.956434	12.5
5	10.8871	16.66667	2.020427	0
6	13.89264	38.09524	4.698982	37.5
7	10.92261	17.3913	1.450642	0
8	10.4047	16.66667	3.469907	16.66667
9	7.160427	25	7.912791	21.4
10	15.94094	32	5.026928	21
11	10.1423	21.73913	3.313081	16.7
N	11	11	11	11
Minimum	7.160427	13.04348	1.450642	0
Maximum	15.94094	42.10526	7.912791	37.5
Mean	11.26362	24.37264	3.998406	17.8697
Std. Error	0.689502	2.901428	0.563438	3.411453
Std. Deviation	2.286819	9.622946	1.868713	11.31451
CV	20.3027	39.48258	46.73645	63.31673
Variability	moderate	High	High	High

Source: Compiled from survey Data

Table XXII: Generalization of Classification Scores

sample number	No	Yes	Overall Percent	No	Yes	Overall Percent
1	61.53846	83.33333	72	100	50	60
2	81.81818	83.33333	82.6087	80	66.66667	75
3	11.11111	100	57.89474	0	87.5	70
4	81.81818	91.66667	86.95652	66.66667	100	87.5
5	80	85.71429	83.33333	100	100	100
6	80	83.33333	81.81818	100	75	88.88889

7	72.72727	91.66667	82.6087	100	100	100
8	87.5	81.25	83.33333	75	100	83.33333
9	80	71.42857	75	66.66667	66.66667	66.66667
10	63.63636	71.42857	68	33.33333	50	42.85714
11	87.5	73.33333	78.26087	75	0	60
N	11	11	11	11	11	11
Minimum	11.11111	71.42857	57.89474	0	0	42.85714
Maximum	87.5	100	86.95652	100	100	100
Mean	71.60451	83.3171	77.43767	72.42424	72.34848	75.84055
Std. Error	6.571946	2.713803	2.59366	9.511725	9.338485	5.425891
Std. Deviation	21.79668	9.000665	8.602198	31.54682	30.97225	17.99564
CV	30.44038	10.8029	11.10854	43.55837	42.80981	23.72826
Variability	high	Low	moderate	High	high	High

Source: Compiled from survey Data

Table XXIII: Generalisation of Independent Variable Importance Scores

sample number	Gender	Marital status	Approximate total annual income (including all sources)	Age	Number of dependent(s)	Years of Experience (number of years)	loss aversion score
1	0.039322	0.118372	0.13896	0.271743	0.256254	0.10514	0.070208
2	0.082308	0.131983	0.178423	0.035444	0.226564	0.178459	0.166819
3	0.188611	0.036886	0.192463	0.033365	0.228836	0.181912	0.137926
4	0.100481	0.079609	0.13131	0.298405	0.229443	0.069719	0.091033
5	0.007362	0.141644	0.032656	0.413267	0.268797	0.136273	0.007362
6	0.007752	0.003001	0.138413	0.310315	0.005224	0.149515	0.38578
7	0.080946	0.10131	0.115507	0.194854	0.285539	0.061147	0.160695
8	0.026701	0.025729	0.066885	0.212468	0.372624	0.251432	0.04416
9	0.062707	0.030511	0.189895	0.187757	0.172193	0.124583	0.232354
10	0.029507	0.125075	0.06107	0.05367	0.179611	0.250542	0.300524
11	0.100645	0.109149	0.234493	0.204858	0.097931	0.154468	0.098456
N	11	11	11	11	11	11	11
Minimum	0.007362	0.003001	0.032656	0.033365	0.005224	0.061147	0.007362
Maximum	0.188611	0.141644	0.234493	0.413267	0.372624	0.251432	0.38578
Mean	0.066031	0.082116	0.134552	0.201468	0.211183	0.151199	0.15412
Std. Error	0.016052	0.014907	0.018853	0.036813	0.029478	0.01893	0.034303
Std. Deviation	0.053237	0.04944	0.062529	0.122095	0.097769	0.062783	0.11377
CV	80.62404	60.20803	46.4715	60.60292	46.29557	41.52313	73.81932
Variability	High	High	High	High	high	high	high

Source: Compiled from survey Data

sample number	Gender	Marital status	Approximate total annual income (including all sources)	Age	Number of dependent(s)	Years of Experience (number of years)	loss aversion score
1	14.47046	43.56044	51.1366	100	94.30028	38.69095	25.83606
2	36.32864	58.25393	78.75171	15.64403	100	78.7674	73.62976
3	82.42179	16.11906	84.10528	14.58044	100	79.49463	60.27292
4	33.67267	26.67816	44.00394	100	76.89008	23.36403	30.50669

Journal of Informatics Education and Research
ISSN: 1526-4726
Vol 5 Issue 1 (2025)

5	1.781503	34.2743	7.901905	100	65.04202	32.97464	1.781503
6	2.009479	0.777997	35.87887	80.43839	1.354065	38.75655	100
7	28.34856	35.48036	40.45226	68.24078	100	21.41469	56.27789
8	7.165746	6.90472	17.94982	57.01951	100	67.47619	11.85109
9	26.98752	13.13143	81.72652	80.80628	74.108	53.61782	100
10	9.818577	41.6191	20.3213	17.85872	59.76586	83.36847	100
11	42.92015	46.54688	100	87.36217	41.76269	65.873	41.98666
N	11	11	11	11	11	11	11
Minimum	1.781503	0.777997	7.901905	14.58044	1.354065	21.41469	1.781503
Maximum	82.42179	58.25393	100	100	100	83.36847	100
Mean	25.99319	29.39512	51.11165	65.63185	73.92936	53.07258	54.74023
Std. Error	7.105267	5.486208	9.288756	10.41568	9.4021	6.972888	10.77227
Std. Deviation	23.5655	18.19569	30.80732	34.54489	31.18324	23.12645	35.72759
CV	90.6603	61.90038	60.27455	52.63434	42.17977	43.57514	65.26751
Variability	high	High	High	high	high	high	high

Source: Compiled from survey Data

From the above mean, standard deviations and coefficient of variation¸ derived based 11 times neural network analysis on the different sets of sample data revealed that there exists external validity of the model applied. Thus, is evident model is stable with variations of samples which were generated by bootstrapping. This further says that findings that loss aversion bias stands before income but after the age and size of family members.

6. Discussion

It has been found that the degree to which loss aversion bias influences the selection of life insurance policies and loss aversion bias predicts the likelihood of policy selection or non-selection as it was derived from the evaluation of the model including the internal consistency and generalization, there exists a predictive capability of a neural network model in understanding the non-linear relationships between loss aversion bias and life insurance product selection where profiles of the decision makers are acting as mediating variable. More pertinently, neural networks can be applied to small-sized sample-based studies and they reveal similar findings compared to the large sample-based studies. This is proved as loss aversion bias has more impact on policy choice than that of income from all sources [including from insurance maturity and bonus]. Loss aversion bias significantly influences life insurance decision-making by emphasizing the avoidance of potential losses over potential gains. This study highlights how insurers use this bias to design products that appeal to loss-averse consumers and how cultural, psychological, and technological factors shape these decisions. This bias leads consumer to prefer avoiding losses over acquiring equivalent gains, impacting their choices in selecting life insurance policies or packages. Thus, there exists a Role of Loss Aversion Bias in Loss aversion effort while Buying Life Insurance Product.

7. Limitations: Small sample sizes can still lead to biased factor loading and reliability estimates. Issues like types of life insurance products with varying levels of coverage, premium costs, and benefits. Health Status and Education Level were not studied and may be considered with larger samples.

8. Scope of the future study: [1] Role Technological and Digital Platform Influences on Loss Aversion [2] Exploration of how digital and AI-driven insurance platforms affect loss aversion in decision-making. [3] The impact of real-time data, personalized recommendations, and digital nudges in shaping insurance purchasing behaviour. [4] Regulatory and Policy Implications of Loss Aversion in Insurance Markets.

9. Conclusion

This research framework provides a comprehensive approach to studying the impact of loss aversion bias on life insurance product selection using neural network analysis and bootstrapping. By focusing exclusively on loss aversion as a latent variable, along with a few selective demographic profiles, the study aimed to provide deeper insights into the cognitive processes that drive consumer behaviour in the life insurance market. The findings are valuable for both academic research in behavioural finance and practical applications in the insurance industry.

Conflict of interest Statement

The authors declare that there are no conflicts of interest associated with this research titled, **"A Study of the Role of Loss Aversion Bias in Loss Aversion Effort in Buying Life Insurance Product."** The study was conducted independently of any direct financial relationships with entities in the life insurance or behavioral finance industries. The authors do not hold personal financial interests in life insurance products or related businesses that could have influenced the research outcomes. All findings are presented objectively, with a focus on advancing academic understanding and providing unbiased insights for practical applications in the insurance selection.

References

- Ainia, N. S. N., & Lutfi, L. (2019). The influence of risk perception, risk tolerance, overconfidence, and loss aversion towards investment decision making. Journal of Economics, Business, & Accountancy Ventura, 21(3), 401-413.
- Bejou, D., Wray, B., & Ingram, T. N. (1996). Determinants of relationship quality: an artificial neural network analysis. Journal of business research, 36(2), 137-143.
- Bihari, A., Dash, M., Muduli, K., Kumar, A., Mulat-Weldemeskel, E., & Luthra, S. (2023). Does cognitive biased knowledge influence investor decisions? An empirical investigation using machine learning and artificial neural network. VINE Journal of Information and Knowledge Management Systems.
- Bormann, C. L., Thirumalaraju, P., Kanakasabapathy, M. K., Kandula, H., Souter, I., Dimitriadis, I., ... & Shafiee, H. (2020). Consistency and objectivity of automated embryo assessments using deep neural networks. Fertility and sterility, 113(4), 781-787.
- Canessa, N., Crespi, C., Motterlini, M., Baud-Bovy, G., Chierchia, G., Pantaleo, G., ... & Cappa, S. F. (2013). The functional and structural neural basis of individual differences in loss aversion. Journal of Neuroscience, 33(36), 14307-14317.
- Carney, J. G., Cunningham, P., & Bhagwan, U. (1999, July). Confidence and prediction intervals for neural network ensembles. In IJCNN'99. International Joint Conference on Neural Networks. Proceedings (Cat. No. 99CH36339) (Vol. 2, pp. 1215-1218). IEEE.
- Choi, B. S. (2016). An overview of bootstrapping method applicable to survey researches in rehabilitation science. Physical Therapy Korea, 23(2), 93-99.
- Cummins, J. D., Smith, B. D., Vance, R. N., & Vanderhel, J. L. (Eds.). (2013). Risk classification in life insurance (Vol. 1). Springer Science & Business Media.
- D'souza, R. N., Huang, P. Y., & Yeh, F. C. (2020). Structural analysis and optimization of convolutional neural networks with a small sample size. Scientific reports, 10(1), 834.
- Dash, G., & Im, J. (2018). Determinants of life insurance demand: Evidences from India. Asia Pacific Journal of Advanced Business and Social Studies, 4(2), 86-99.
- Do Hwang, I. (2021). Prospect theory and insurance demand: Empirical evidence on the role of loss aversion. Journal of Behavioral and Experimental Economics, 95, 101764.
- Do Hwang, I. (2024). Behavioral aspects of household portfolio choice: Effects of loss aversion on life insurance uptake and savings. International Review of Economics & Finance, 89, 1029-1053.
- Duarte, I., Pinheiro, D., Pinto, A. A., & Pliska, S. R. (2011). An overview of optimal life insurance purchase, consumption and investment problems. Dynamics, Games and Science I: DYNA 2008, in Honor of Maurício Peixoto and David Rand, University of Minho, Braga, Portugal, September 8-12, 2008, 271-286.
- Feng, S., Zhou, H., & Dong, H. (2019). Using deep neural network with small dataset to predict material defects. Materials & Design, 162, 300-310.
- Ferber, P., Geißer, F., Trevizan, F., Helmert, M., & Hoffmann, J. (2022, June). Neural network heuristic functions for classical planning: Bootstrapping and comparison to other methods. In Proceedings of the International Conference on Automated Planning and Scheduling (Vol. 32, pp. 583-587).
- Franke, J., & Neumann, M. H. (2000). Bootstrapping neural networks. Neural computation, 12(8), 1929-1949.

- Ghasemi, F., Mehridehnavi, A., Pérez-Garrido, A., & Pérez-Sánchez, H. (2018). Neural network and deep-learning algorithms used in QSAR studies: merits and drawbacks. Drug discovery today, 23(10), 1784-1790.
- Gökhan, A. K. S. U., Güzeller, C. O., & Eser, M. T. (2019). The effect of the normalization method used in different sample sizes on the success of artificial neural network model. International journal of assessment tools in education, 6(2), 170-192.
- Golden, R. M. (1996). Mathematical methods for neural network analysis and design. MIT Press.
- Hillis, D. M., & Bull, J. J. (1993). An empirical test of bootstrapping as a method for assessing confidence in phylogenetic analysis. Systematic biology, 42(2), 182-192.
- Huang, C., & Moraga, C. (2004). A diffusion-neural-network for learning from small samples. International Journal of Approximate Reasoning, 35(2), 137-161.
- Kokmotou, K., Cook, S., Xie, Y., Wright, H., Soto, V., Fallon, N., ... & Stancak, A. (2017). Effects of loss aversion on neural responses to loss outcomes: An event-related potential study. Biological Psychology, 126, 30-40.
- Kornblith, S., Norouzi, M., Lee, H., & Hinton, G. (2019, May). Similarity of neural network representations revisited. In International conference on machine learning (pp. 3519-3529). PMLR.
- Krebsbach, C. M. (2013). Bootstrapping with small samples in structural equation modeling: Goodness of fit and confidence intervals. University of Rhode Island.
- Li, Z., Liu, F., Yang, W., Peng, S., & Zhou, J. (2021). A survey of convolutional neural networks: analysis, applications, and prospects. IEEE transactions on neural networks and learning systems, 33(12), 6999-7019.
- Liu, B., Wei, Y., Zhang, Y., & Yang, Q. (2017, August). Deep Neural Networks for High Dimension, Low Sample Size Data. In IJCAI (Vol. 2017, pp. 2287-2293).
- Macas, M., Moretti, F., Fonti, A., Giantomassi, A., Comodi, G., Annunziato, M., ... & Capra, A. (2016). The role of data sample size and dimensionality in neural network based forecasting of building heating related variables. Energy and Buildings, 111, 299-310.
- Madhiarasan, M., & Louzazni, M. (2022). Analysis of artificial neural network: architecture, types, and forecasting applications. Journal of Electrical and Computer Engineering, 2022(1), 5416722.
- Nixon, J., Lakshminarayanan, B., & Tran, D. (2020). Why are bootstrapped deep ensembles not better?. In "I Can't Believe It's Not Better!"NeurIPS 2020 workshop.
- Paposa, S. S., Ukinkar, V. G., & Paposa, K. K. (2019). Service quality and customer satisfaction: Variation in customer perception across demographic profiles in life insurance industry. International journal of innovative technology and exploring engineering, 8(10), 3767-3775.
- Poh, N., Martin, A., & Bengio, S. (2005). Performance Generalization in Biometric Authentication Using Joint User-Specific and Sample Bootstraps.
- Poh, N., Martin, A., & Bengio, S. (2007). Performance generalization in biometric authentication using joint user-specific and sample bootstraps. IEEE transactions on pattern analysis and machine intelligence.
- Ramij, G. (2021). Factors shaping consumers intention in purchasing life insurance policy in Bangladesh: A binary logistic analysis. Journal of Applied Finance and Banking, 11(6), 21-36.
- Reed, S., Lee, H., Anguelov, D., Szegedy, C., Erhan, D., & Rabinovich, A. (2014). Training deep neural networks on noisy labels with bootstrapping. arXiv preprint arXiv:1412.6596.
- Shaikhina, T., & Khovanova, N. A. (2017). Handling limited datasets with neural networks in medical applications: A small-data approach. Artificial intelligence in medicine, 75, 51-63.
- Smys, S., Chen, J. I. Z., & Shakya, S. (2020). Survey on neural network architectures with deep learning. Journal of Soft Computing Paradigm (JSCP), 2(03), 186-194.
- Tati, R. K., & Baltazar, E. B. B. (2018). Factors influencing the choice of investment in life insurance policy. Theoretical Economics Letters, 8(15), 3664.
- Thaler, R. H. (1999). Mental accounting matters. Journal of Behavioral decision making, 12(3), 183-206.
- Thaler, R. H. (2017). Behavioral economics. Journal of Political Economy, 125(6), 1799-1805.
- Tom, S. M., Fox, C. R., Trepel, C., & Poldrack, R. A. (2007). The neural basis of loss aversion in decision-making under risk. Science, 315(5811), 515-518.
- Tu, J. V. (1996). Advantages and disadvantages of using artificial neural networks versus logistic regression for predicting medical outcomes. Journal of clinical epidemiology, 49(11), 1225-1231.
- Twomey, J. M., & Smith, A. E. (1995). Performance measures, consistency, and power for artificial neural network models. Mathematical and computer modelling, 21(1-2), 243-258.

- Ueda, N., & Nakano, R. (1995, November). Estimating expected error rates of neural network classifiers in small sample size situations: a comparison of cross-validation and bootstrap. In Proceedings of ICNN'95-International Conference on Neural Networks (Vol. 1, pp. 101-104). IEEE.
- Ungarelli, D. L. (1984). Insurance and prevention: why and how?.
- White, H. (1989). Learning in artificial neural networks: A statistical perspective. Neural computation, 1(4), 425-464.
- Wray, B., Palmer, A., & Bejou, D. (1994). Using neural network analysis to evaluate buyer-seller relationships. European journal of Marketing, 28(10), 32-48.
- Yan, L., Han, X., He, B., & Sun, L. (2020, April). End-to-end bootstrapping neural network for entity set expansion. In Proceedings of the AAAI conference on artificial intelligence (Vol. 34, No. 05, pp. 9402-9409).Page 668 of 17
- Yoon, Y., Swales Jr, G., & Margavio, T. M. (1993). A comparison of discriminant analysis versus artificial neural networks. Journal of the Operational Research Society, 44(1), 51-60.
- Yung, Y. F., & Bentler, P. M. (2013). Bootstrapping techniques in analysis of mean and covariance structures. In Advanced structural equation modeling (pp. 195-226). Psychology Press.
- Zeng, J., Wang, Y., Zeng, J., Cao, Z., Chen, H., Liu, Y., ... & Su, L. (2019). Predicting the behavioural tendency of loss aversion. Scientific Reports, 9(1), 5024.
- Zoubir, A. M., & Iskandler, D. R. (2007). Bootstrap methods and applications. IEEE Signal Processing Magazine, 24(4), 10-19.