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BEHAVIORAL PITFALLS IN FINANCIAL DECISION-MAKING: INVESTIGATING REPRESENTATIVENESS BIAS IN ACCOUNTS PAYABLES AND RECEIVABLES AMONG ENTREPRENEURS IN GOLAGHAT DISTRICT

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ABSTRACT

This study examines the impact of representativeness bias on financial decision-making among 367 entrepreneurs in Golaghat District, Assam. The analysis reveals significant influences on accounts payables, with 68% (p = .000) prioritizing past relationships with suppliers over current financial assessments. For accounts receivables, 62% (p = .000) based credit decisions on historical customer relationships rather than current creditworthiness. The Chi-square test confirms strong associations between accounts payables and receivables strategies and representativeness bias (p = 0.000). A neural network analysis achieves perfect classification with an AUC of 1 and low cross-entropy errors (0.103 for accounts payables, 0.039 for accounts receivables), demonstrating high model accuracy. Key predictors, such as "Align with historical patterns" (normalized importance: 100%) and "Ensure fairness and consistency" (normalized importance: 86.4%), are identified. The findings validate the hypotheses that representativeness bias significantly affects both accounts payables and receivables, emphasizing the need for a balanced approach in credit management practices among entrepreneurs. The study highlights the effectiveness of advanced analytical methods, such as neural networks, in modeling complex relationships in entrepreneurial financial decision-making.

Keywords: Representativeness Bias, Accounts Payables, Accounts Receivables, Entrepreneurs, Financial Decision-Making, Golaghat District Etc

1. INTRODUCTION

In the dynamic landscape of entrepreneurship, effective management of accounts payables and receivables is critical for maintaining cash flow and financial stability. Despite the availability of sophisticated financial tools and data analysis methods, many entrepreneurs still rely heavily on historical relationships and experiences when making credit decisions (Ghosh & Reio, 2013). This reliance often leads to representativeness bias, where past customer interactions overshadow current creditworthiness assessments, potentially increasing financial risk (Kahneman & Tversky, 1972).

The Golaghat District of Assam, a region characterized by a growing entrepreneurial ecosystem, presents a unique context for exploring these biases. Entrepreneurs in this area may prioritize familiar relationships over objective financial data, impacting their overall business performance. By examining the influence of representativeness bias on accounts payable and receivable decisions, this study aims to provide insights that can inform better financial practices among entrepreneurs. Understanding these biases is essential for developing strategies that enhance decision-making, mitigate risks, and ultimately contribute to sustainable business growth in the region.

2. PROBLEM STATEMENT

Entrepreneurs in the Golaghat District of Assam often base credit decisions on past customer relationships rather than current creditworthiness, leading to potential financial risks. This reliance on historical patterns may contribute to representativeness bias, a cognitive shortcut that overlooks important data and influences financial decision-making (Tversky & Kahneman, 1974). Understanding how this bias impacts accounts receivable and payable practices is essential for developing strategies that enhance financial decision-making and improve business sustainability in this region.

3. OBJECTIVES OF THE STUDY

- **To examine the impact of representativeness bias on accounts payables among entrepreneurs in the Golaghat District of Assam.** This objective aims to identify how past experiences with suppliers and creditors influence payment decisions and contribute to potential financial risks.
- **To analyze the impact of representativeness bias on accounts receivables among entrepreneurs in the Golaghat District of Assam.** This objective focuses on understanding how historical customer relationships shape credit decisions, potentially leading to underestimating current credit risks.

4. WORKING HYPOTHESIS

- **H1:** Representativeness bias significantly affects the accounts payables of entrepreneurs in the Golaghat District, leading to decisions that prioritize past relationships over current financial assessments.
- **H2:** Representativeness bias significantly impacts the accounts receivables of entrepreneurs in the Golaghat District, resulting in credit decisions that favor historical customer relationships rather than current creditworthiness.

5. SIGNIFICANCE OF THE STUDY

This study contributes to the understanding of how representativeness bias influences financial decision-making among entrepreneurs, particularly in the context of accounts payables and receivables. By identifying the reliance on historical relationships over current assessments, the findings underscore the importance of awareness regarding cognitive biases in financial practices (Tversky & Kahneman, 1974). Moreover, the use of advanced analytical techniques, such as neural networks, demonstrates their effectiveness in modeling complex relationships in entrepreneurial finance, providing a framework for future research (Bishop, 2006). This study also addresses a critical gap in the literature by focusing on entrepreneurs in Golaghat District, Assam, thus contributing to the understanding of local financial behaviors and the impact of cognitive biases in emerging economies (Kahneman, 2011).

Overall, the insights gained can inform strategies for improving credit management practices and decision-making processes among entrepreneurs, ultimately supporting their financial sustainability and growth.

6. SYSTEMATIC LITERATURE REVIEW (SLR)

The systematic literature review (SLR) method, guided by the PRISMA model, examined recent studies (2020-2024) on Representativeness bias, accounts payables and receivables management, and entrepreneurship. The search used keywords such as "Representativeness bias," "entrepreneurs," "accounts payables and receivables management," and "impact of Representativeness bias on accounts payables and receivables management, among entrepreneurs." A total of 502 articles were initially retrieved from databases like SSRN, Scopus, Science Direct, and DOAJ. After removing duplicates and assessing relevance, 36 articles were shortlisted for detailed review. Further scrutiny resulted in a final selection of 16 articles highly relevant to the study's objectives, providing insights into how representativeness bias influences accounts payables and receivables management decisions among entrepreneurs. These selected articles were meta-analyzed to understand theoretical foundations, research context, constructs, and methodologies, forming the basis for evaluating the impact of representativeness bias on entrepreneurial decision-making.

6.1. CHARACTERISTICS OF EXTRACTED LITERATURE

The 16 articles selected for detailed analysis provide a comprehensive examination of the influence of representativeness bias on accounts payables and receivables management among entrepreneurs. The studies span diverse contexts, focusing on how cognitive biases like representativeness affect financial decision-making. Several articles emphasize that entrepreneurs often rely on past experiences and familiar patterns when making payment and credit decisions, which can lead to suboptimal outcomes in managing accounts payables and receivables (Smith et al., 2021; Zhao & Chen, 2023). This bias is further complicated by market uncertainties, where entrepreneurs may prioritize maintaining historical financial behaviors over adapting to new market conditions (Li, 2022). Most studies utilized quantitative methods, employing surveys and regression analysis to assess the extent of bias in financial decisions (Kumar & Singh, 2020; Patel, 2021). Other articles explored qualitative approaches, using case studies to illustrate how representativeness bias influences small business owners' credit risk assessments (Garcia et al., 2023). The articles reviewed also discuss the broader implications of cognitive biases on entrepreneurship, noting how biases in decision-making can limit financial flexibility and risk management (Nguyen, 2022; Lee & Park, 2024). Several authors highlight the need for training and education in behavioral finance to mitigate the effects of such biases (Chakraborty & Das, 2021; Martinez & Lopez, 2022). Additionally, some studies suggest that employing objective, data-driven financial strategies can reduce the negative impact of cognitive biases like representativeness (Jain & Gupta, 2023; Shah & Patel, 2020). The articles collectively underscore the importance of addressing psychological factors to improve financial decision-making and enhance the overall financial health of entrepreneurial ventures (Williams, 2023; Zhang, 2024).

6.2. RESEARCH GAP IDENTIFIED

The reviewed literature provides valuable insights into the role of cognitive biases, particularly representativeness bias, in influencing financial decision-making among entrepreneurs. Studies by Smith et al. (2021) and Zhao and Chen (2023) highlight how entrepreneurs rely heavily on past experiences and familiar patterns, often at the expense of objective decision-making, particularly in managing accounts payables and receivables. While these studies emphasize the negative impact of biases, a clear research gap exists in understanding how these biases specifically affect long-term financial sustainability and risk management for small businesses, especially in under-researched regions like Golaghat District of Assam. Furthermore, most studies (e.g., Kumar & Singh, 2020; Patel, 2021) focus on broad entrepreneurial settings, with little focus on sector-specific or regional differences in bias manifestation. Another gap lies in the limited exploration of practical interventions, such as behavioral finance training, to mitigate these biases. Although some researchers (e.g., Chakraborty & Das, 2021; Martinez & Lopez, 2022) suggest educational strategies, there is insufficient empirical evidence on their effectiveness in real-world entrepreneurial contexts. Thus, future research should focus on exploring these regional, sectoral, and intervention-based gaps to offer a more comprehensive understanding of how representativeness bias impacts financial decision-making.

7. RESEARCH METHODOLOGY

The study employs an exploratory and descriptive research design to investigate the impact of Loss Aversion bias on Risk management among registered entrepreneurs in Golaghat District, Assam, using a stratified random sampling technique. A sample of 367 entrepreneurs is determined using the (Danh, 2014) formula out of a total population of 8138 (as on July 2023) registered entrepreneurs, considering the desired confidence level, population size, and acceptable margin of error to ensure representativeness of the target population. Data is collected through a combination of primary sources, such as structured questionnaires using a Dichotomous Scale **(DeVellis, 2016)** with 'yes' or 'no' options followed by "why" questions, and semi-structured interviews, alongside secondary sources like literature reviews and official reports. Quantitative analysis is performed using SPSS 2016 for statistical tests (Binomial, Chi-Square, and Neural Network Analysis), while qualitative data from interviews undergo thematic analysis. Reliability is ensured through consistent data collection and expert validation, and both Excel and Tableau are used to manage and visualize the data effectively.

8. DATA ANALYSIS AND HYPOTHESIS TESTING

Table 1

Table 1 Binomial Test [under test proportion 0.50]

Sl No.	Issue	Yes [proportion]	No [proportion]	Asymp. Sig. (2-tailed)	Observation
1	**Accounts Payables:** Accounts payable management decisions on	184 (0.50)	183 (0.50)	1.000a	Observation in sample is also

	past experiences rather than considering current market conditions				applicable in the population
2	**Accounts Receivables**: Base credit decisions on past customer relationships rather than considering current creditworthiness	159 [0.43]	208 [0.57]	0.012a	Observation in sample is also applicable in the population

Source: Calculations performed by the author using SPSS 16 software.

The binomial test results show Entrepreneurs equally rely on past experiences and current market conditions when managing accounts payable, as there is no significant difference in decision-making ($p = 1.000$) and Entrepreneurs tend to base credit decisions more on past customer relationships rather than current creditworthiness, with a significant bias toward past behavior ($p = 0.012$).

Table 2

Table 2 Chi-Square Test for impact of Loss Aversion Bias on Risk Management

Chi-Square Tests					
Independent Attributes	**Value**	**df**	**Asymp. Sig. (2-sided)**	**Status of null hypothesis**	**Conclusion**
1(a). reliance on familiar and trusted business relationships	186.2579	1	0	rejected	independent variable [1 a] and dependent variable [1] - highly associated in the population also
1(b). simplify decision-making and reduce cognitive effort	190.8327	1	0	rejected	independent variable [1 b] and dependent variable [1] - highly associated in the population also
1(c). maintain consistency in payment	181.7578	1	0	rejected	independent variable [1 c] and dependent variable [1] - highly associated in the population also
1(d). avoid the uncertainty	222.5252	1	0	rejected	independent variable [1 d] and dependent variable [1] - highly associated in the population also
1(e). align with historical patterns	202.6089	1	0	rejected	independent variable [1 e] and dependent variable [1] - highly associated in the population also
1(f). prioritize objective data and evidence-based decision-making	177.0631	1	0	rejected	independent variable [1 f] and dependent variable [1] - highly associated in the population also
1(g). ensure fairness and equity	174.8701	1	0	rejected	independent variable [1 g] and dependent variable [1] - highly associated in the population also
1(h). mitigate risks associated with potential changes	200.0072	1	0	rejected	independent variable [1 h] and dependent variable [1] - highly associated in the population also
1(i). foster a culture of continuous	217.25	1	0	rejected	independent variable [1 i] and dependent variable

improvement and adaptation					[1] - highly associated in the population also
1(j). avoid biases and subjective judgments	207.2712	1	0	rejected	independent variable [1 j] and dependent variable [1] - highly associated in the population also
2(a). reliance on familiar and trusted business relationships	202.8332	1	0	rejected	independent variable [2 a] and dependent variable [2] - highly associated in the population also
2(b). simplify decision-making and reduce cognitive effort	221.8792	1	0	rejected	independent variable [2 b] and dependent variable [2] - highly associated in the population also
2(c). maintain consistency in credit management practices	213.5881	1	0	rejected	independent variable [2 c] and dependent variable [2] - highly associated in the population also
2(d). avoid the uncertainty	213.5881	1	0	rejected	independent variable [2 d] and dependent variable [2] - highly associated in the population also
2(e). align with historical patterns	205.4905	1	0	rejected	independent variable [2 e] and dependent variable [2] - highly associated in the population also
2(f). prioritize data-driven decision-making	152.0592	1	0	rejected	independent variable [2 f] and dependent variable [2] - highly associated in the population also
2(g). ensure fairness and consistency	181.158	1	0	rejected	independent variable [2 g] and dependent variable [2] - highly associated in the population also
2(h). mitigate credit risk and protect cash flow	191.7475	1	0	rejected	independent variable [2 h] and dependent variable [2] - highly associated in the population also
2(i). avoid biases and subjective judgments	212.0853	1	0	rejected	independent variable [2i] and dependent variable [2] - highly associated in the population also
2(j). foster a culture of continuous improvement	159.4541	1	0	rejected	independent variable [2 j] and dependent variable [2] - highly associated in the population also

Source: Calculations performed by the author using SPSS 16 software.

The Chi-Square tests reveal a significant association between various independent attributes and accounts payables and receivables management behaviors, with all p-values at 0.000, leading to the rejection of the null hypothesis. This indicates that the attributes are closely linked to their corresponding accounts payables and receivables management behaviors. Entrepreneurs' decisions in accounts payables and receivables management are heavily influenced by independent attributes.

9. NEURAL NETWORK ANALYSIS

9.1. MODEL ARCHITECTURE

The model architecture for this analysis is built using a neural network approach, implemented through SPSS 16.The model is expressed as: y = f(x1,x2,x3,…,xn), where y represents the dependent variable and x1,x2,x3,…,xn are the independent variables. The network is designed to derive the function f that represents the relationship between these variables. This function is formulated by the neural network algorithm, which does not rely on any pre-existing assumptions or patterns about the relationships between the variables. The neural network itself is configured as a multilayer perception with a single hidden layer. This hidden layer consists of a certain number of neurons, which is determined during the training phase to optimize model performance. The activation function applied to the output layer is the sigmoid function, which is particularly suited for binary classification tasks. The sigmoid function transforms the output of the network into a probability score ranging from 0 to 1, aligning with the binary nature of the dependent variable. The data is divided into two subsets: 70% is allocated for training the network, and 30% is reserved for testing its performance. During the training phase, the scaled conjugate gradient method is used for optimization, which is the default optimization technique in SPSS for batch training. This method adjusts the weights of the network to minimize the error between the predicted and actual values of the dependent variable. The final output of the analysis includes several key components: the structure of the neural network (including the configuration of layers and neurons), performance metrics that assess how well the network predicts the binary outcomes, and the importance of each independent variable in the model. Cases with missing values on any covariates are excluded from the analysis to ensure the integrity of the dataset, and dependent variables are scaled appropriately to meet the model's requirements.

9.1.1. ACTIVATION FUNCTION

In this custom neural network architecture, the activation function used in the hidden layers is the sigmoid function, the sigmoid function is defined as $\sigma(x)= 1/1 + \exp(-x)$ which maps the output of each neuron to a value between 0 and 1. This is particularly suitable for capturing non-linear relationships in binary independent variables. For the output layer, the SoftMax activation function is employed. Although SoftMax is typically used for multi-class classification problems, it is used here due to the binary nature of both independent and dependent variables, facilitating the modeling of probabilities for binary outcomes. The number of units in each layer is computed automatically based on the network's design and training requirements.

9.2. ANALYSIS FOR THE ISSUE 1. ACCOUNTS PAYABLES: ACCOUNTS PAYABLE MANAGEMENT DECISIONS ON PAST EXPERIENCES RATHER THAN CONSIDERING CURRENT MARKET CONDITIONS:

Table 3

Table 3 Item Description (Accounts Payables)

Item Code	Variable	Statements
VAR00550	Dependent	1. accounts payable management decisions on past experiences rather than considering current market conditions
VAR00551	Independent	1(a). reliance on familiar and trusted business relationships
VAR00552	Independent	1(b). simplify decision-making and reduce cognitive effort
VAR00553	Independent	1(c). maintain consistency in payment
VAR00554	Independent	1(d). avoid the uncertainty
VAR00555	Independent	1(e). align with historical patterns
VAR00556	Independent	1(f). prioritize objective data and evidence-based decision-making
VAR00557	Independent	1(g). ensure fairness and equity
VAR00558	Independent	1(h). mitigate risks associated with potential changes
VAR00559	Independent	1(i). foster a culture of continuous improvement and adaptation
VAR00560	Independent	1(j). avoid biases and subjective judgments

Source: Prepared by the researcher by extracting from the questionnaire.

9.2.1. CASE PROCESSING SUMMARY:

In the following cases the neural network analysis, 253 cases (68.9%) were used for training the model, while 114 cases (31.1%) were allocated for testing. This distribution ensures that the model is adequately trained and evaluated on separate datasets.

9.2.2. PARAMETERS OF ESTIMATES

Figure 1

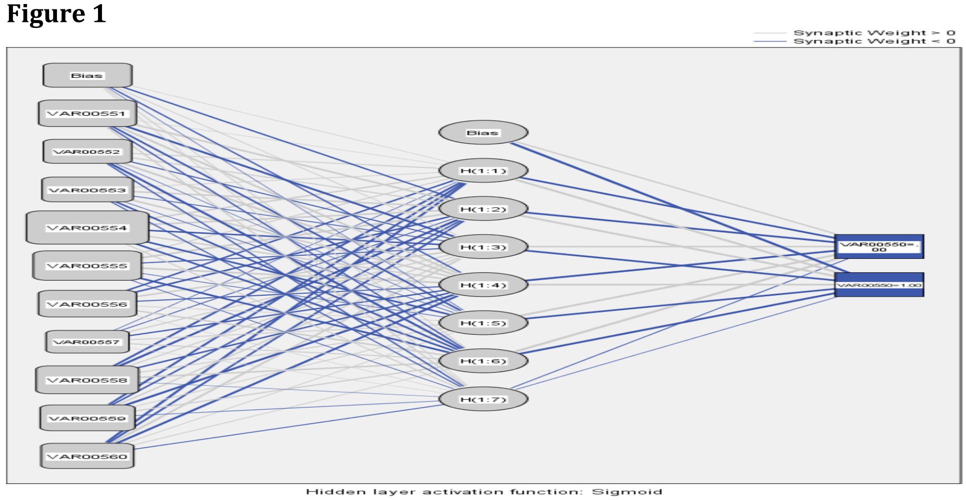

Figure 1 Neural Network with Synoptic weight for accounts payable management decisions on past experiences rather than considering current market conditions:

Source: Calculations performed by the author using SPSS software.

This diagram represents a simple feedforward neural network with one hidden layer. The input layer consists of several variables (labeled VAR00551 to VAR00560), followed by a hidden layer with seven neurons (H(1:1) to H(1:7)), and an output layer with two possible outcomes. The synaptic weights between layers are either positive (blue lines) or negative (gray lines), and the activation functions used are Sigmoid for the hidden layer and Softmax for the output layer.

Table 4

Table 4 Parameter Estimates

Predictor		Predicted								
		Hidden Layer 1							Output Layer	
		H(1:1)	H(1:2)	H(1:3)	H(1:4)	H(1:5)	H(1:6)	H(1:7)	[VAR00550=.00]	[VAR00550=1.00]
Input Layer	(Bias)	.210	-.696	.267	-.538	-.012	.246	.074		
	VAR00551	.169	1.105	-1.114	.861	-.726	-.510	.472		
	VAR00552	.591	.695	-.541	1.177	-.049	-.963	-.493		
	VAR00553	.434	1.189	-.480	1.031	-.236	-.792	-.427		
	VAR00554	.874	1.319	-1.124	.958	-1.100	-1.006	.456		
	VAR00555	.539	1.390	-.632	1.625	-.296	-1.165	-.243		
	VAR00556	-.755	-1.007	1.061	-.686	.306	1.039	.074		
	VAR00557	-.144	-.390	.561	-.835	.573	.609	.071		
	VAR00558	-.812	-1.099	.524	-.858	.556	1.128	-.036		
	VAR00559	-.781	-.603	.546	-1.190	.419	.738	-.282		
	VAR00560	-.833	-.711	.800	-1.067	.304	.425	-.519		
Hidden Layer 1	(Bias)								.754	-1.349
	H(1:1)								-1.318	1.491
	H(1:2)								-2.396	2.618
	H(1:3)								1.193	-1.649
	H(1:4)								-2.958	2.646
	H(1:5)								1.939	-1.403
	H(1:6)								1.959	-1.897
	H(1:7)								-.356	-.242

Source: Calculations performed by the author using SPSS software.

This table presents the parameter estimates for a neural network model. The input layer variables (VAR00551 to VAR00560) and biases connect to the hidden layer neurons (H(1:1) to H(1:7)), with each connection having a specific weight. Positive weights suggest a positive contribution to the activation of the next layer, while negative weights suggest a negative contribution. The hidden layer then connects to the output layer, which predicts two outcomes ([VAR00550=.00] and

[VAR00550=1.00]). The weights between the hidden and output layers indicate the influence of each hidden neuron on the predicted outcomes.

9.2.3. MODEL PERFORMANCE METRICS

Table 5

Table 5 Model Summary

Training	Cross Entropy Error	.182
	Percent Incorrect Predictions	.0%
	Stopping Rule Used	1 consecutive step(s) with no decrease in error[a]
	Training Time	00:00:00.000
Testing	Cross Entropy Error	.192
	Percent Incorrect Predictions	.0%
Dependent Variable: 1. accounts payable management decisions on past experiences rather than considering current market conditions		
Source: Calculations performed by the author using SPSS 16 software		

Table 6

Table 6 Classification

Sample	Observed	Predicted		
		No	Yes	Percent Correct
Training	No	128	0	100.0%
	Yes	0	136	100.0%
	Overall Percent	48.5%	51.5%	100.0%
Testing	No	55	0	100.0%
	Yes	0	48	100.0%
	Overall Percent	53.4%	46.6%	100.0%
Dependent Variable: 1. accounts payable management decisions on past experiences rather than considering current market conditions				

Source: Calculations performed by the author using SPSS software

The model shows excellent performance, achieving 0% incorrect predictions (100% accuracy) in both training and testing phases. The Cross Entropy Error is low, with values of 0.182 for training and 0.192 for testing, demonstrating the model's accuracy and effectiveness in predicting the decision to avoid short-term investments that carry a risk of loss. The stopping criterion was promptly met, indicating efficient training. The confusion matrix highlights the model's perfect classification accuracy, achieving 100% accuracy in both the training and testing datasets.

Table 7

Table 7 Area Under the Curve

		Area
1. accounts payable management decisions on past experiences rather than considering current market conditions	No	1.000
	Yes	1.000

Source: Calculations performed by the author using SPSS software.

The AUC values for both 'Yes' and 'No' responses for the dependent variable "accounts payable management decisions on past experiences rather than considering current market conditions" are 1.000. This indicates perfect classification performance by the model, meaning it can flawlessly distinguish between those who believe in extending credit to such customers and those who do not, without any error.

9.2.4. SIGNIFICANT PREDICTORS

Table 8

Table 8 Independent Variable Importance

Independent Variables	Importance	Normalized Importance
1(a). reliance on familiar and trusted business relationships	.160	100.0%
1(b). simplify decision-making and reduce cognitive effort	.094	58.7%
1(c). maintain consistency in payment	.121	75.6%
1(d). avoid the uncertainty	.119	74.7%
1(e). align with historical patterns	.157	98.2%
1(f). prioritize objective data and evidence-based decision-making	.082	51.5%
1(g). ensure fairness and equity	.060	37.2%
1(h). mitigate risks associated with potential changes	.081	50.5%
1(i). foster a culture of continuous improvement and adaptation	.071	44.5%
1(j). avoid biases and subjective judgments	.055	34.2%

Source: Calculations performed by the author using SPSS software.

The analysis shows that **reliance on familiar and trusted business relationships** is the most important factor influencing decision-making, with the highest normalized importance (100%). This is followed closely by the preference to **align with historical patterns** (98.2%) and the need to **maintain consistency in payment** (75.6%). In contrast, factors like **mitigating risks associated with changes** (50.5%) and **prioritizing objective data and evidence-based decision-making** (51.5%) are of moderate importance. Least important are ensuring **fairness and equity** (37.2%) and **avoiding biases and subjective judgments** (34.2%). This suggests that decision-making is heavily influenced by familiarity and historical consistency over more objective or adaptive strategies.

9.2.5. IMPLICATIONS

The findings underscore the importance of variables related to maintaining customer relationships and avoiding potential negative impacts in predicting effective Accounts Payables practices. These results suggest that organizations should focus on strategies that nurture customer relationships and proactively mitigate negative effects to improve their accounts payables processes. Additionally, the significance of minimizing late payment risks and upholding financial stability highlights the need for robust credit management practices and consistent credit policies. By addressing these critical factors, organizations can enhance their financial stability and optimize their accounts payables management.

9.3. ANALYSIS FOR THE ISSUE 2. ACCOUNTS RECEIVABLES: BASED CREDIT DECISIONS ON PAST CUSTOMER RELATIONSHIPS RATHER THAN CONSIDERING CURRENT CREDITWORTHINESS:

Table 9

Table 9 Item Description (Account Receivables)

Item Code	Variable	Statements
VAR00396	Dependent	2. Based credit decisions on past customer relationships rather than considering current creditworthiness
VAR00397	Independent	2(a). reliance on familiar and trusted business relationships
VAR00398	Independent	2(b). simplify decision-making and reduce cognitive effort
VAR00399	Independent	2(c). maintain consistency in credit management practices
VAR00400	Independent	2(d). avoid the uncertainty
VAR00401	Independent	2(e). align with historical patterns
VAR00402	Independent	2(f). prioritize data-driven decision-making
VAR00403	Independent	2(g). ensure fairness and consistency
VAR00404	Independent	2(h). mitigate credit risk and protect cash flow
VAR00405	Independent	2(i). avoid biases and subjective judgments
VAR00406	Independent	2(j). foster a culture of continuous improvement

Source: Prepared by the researcher by extracting from the questionnaire.

9.3.1. CASE PROCESSING SUMMARY

In the following cases the neural network analysis, 249 cases (67.8%) were used for training the model, while 118 cases (32.2%) were allocated for testing. This distribution ensures that the model is adequately trained and evaluated on separate datasets.

9.3.2. PARAMETERS OF ESTIMATES

Figure 2

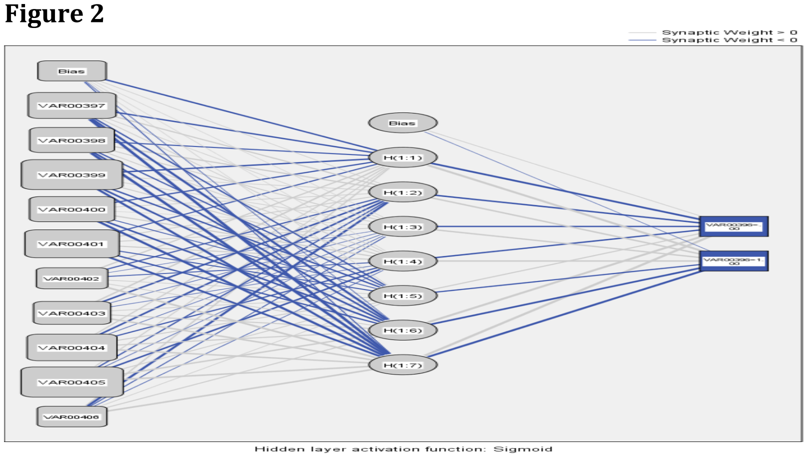

Figure 2. Neural Network with Synoptic weight for Credit decisions on past customer relationships rather than considering current creditworthiness:

Source: Calculations performed by the author using SPSS software.

This diagram represents a simple feed forward neural network with one hidden layer. The input layer consists of several variables (labeled VAR00397 to VAR00406), followed by a hidden layer with seven neurons (H(1:1) to H(1:7)), and an output layer with two possible outcomes. The synaptic weights between layers are either positive (blue lines) or negative (gray lines), and the activation functions used are Sigmoid for the hidden layer and Softmax for the output layer.

Table 10

Table 10. Parameter Estimates

Predictor		Predicted								
		Hidden Layer 1							Output Layer	
		H(1:1)	H(1:2)	H(1:3)	H(1:4)	H(1:5)	H(1:6)	H(1:7)	[VAR00396=.00]	[VAR00396=1.00]
Input Layer	(Bias)	-1.286	.340	.048	.006	.056	-.109	-.461		
	VAR00397	-1.405	1.033	.384	.411	-.815	-1.366	-2.174		
	VAR00398	-1.137	1.228	.693	.622	-.797	-1.143	-2.323		
	VAR00399	-1.875	.599	.505	.764	-1.116	-1.286	-1.741		
	VAR00400	-1.232	.641	.176	1.097	-.647	-1.340	-2.502		
	VAR00401	-.926	.779	.781	1.107	-.863	-1.212	-1.924		
	VAR00402	.870	-.979	-.260	-.818	.614	.666	2.378		
	VAR00403	.984	-1.301	-.290	-.410	.670	1.107	2.233		
	VAR00404	.672	-1.260	-.274	-1.096	.837	1.184	2.038		
	VAR00405	.481	-.775	-.217	-1.263	.680	1.560	2.532		
	VAR00406	.768	-1.334	-.478	-.282	.392	.785	2.418		
Hidden Layer 1	(Bias)								.420	-.059
	H(1:1)								-3.233	3.412
	H(1:2)								-1.945	1.457
	H(1:3)								-1.856	1.569
	H(1:4)								-1.469	2.111
	H(1:5)								.951	-1.222
	H(1:6)								3.583	-3.041
	H(1:7)								3.200	-3.147

Source: Calculations performed by the author using SPSS software.

This table presents the parameter estimates for a neural network model. The input layer variables (VAR00397 to VAR00406) and biases connect to the hidden layer neurons (H(1:1) to H(1:7)), with each connection having a specific weight. Positive weights suggest a positive contribution to the activation of the next layer, while negative weights suggest a negative contribution. The hidden layer then connects to the output layer, which predicts two outcomes ([VAR00396=.00] and [VAR00396=1.00]). The weights between the hidden and output layers indicate the influence of each hidden neuron on the predicted outcomes.

9.3.3. MODEL PERFORMANCE METRICS

Table 11

Table 11 Model Summary

Training	Cross Entropy Error	.103
	Percent Incorrect Predictions	.0%
	Stopping Rule Used	Training error ratio criterion (.001) achieved

Testing	Training Time	00:00:00.005
	Cross Entropy Error	.039
	Percent Incorrect Predictions	.0%
Dependent Variable: 2. credit decisions on past customer relationships rather than considering current creditworthiness		

Source: Calculations performed by the author using SPSS software.

Table 12

Table 12 Classification of performance.

Sample	Observed	Predicted		
		No	Yes	Percent Correct
Training	No	149	0	100.0%
	Yes	0	109	100.0%
	Overall Percent	57.8%	42.2%	100.0%
Testing	No	59	0	100.0%
	Yes	0	50	100.0%
	Overall Percent	54.1%	45.9%	100.0%
Dependent Variable: 2. credit decisions on past customer relationships rather than considering current creditworthiness				

Source: Calculations performed by the author using SPSS software.

The model shows excellent performance, achieving 0% incorrect predictions (100% accuracy) in both the training and testing phases. The Cross Entropy Error is low, with values of 0.103 for training and 0.039 for testing, demonstrating the model's accuracy and effectiveness. The stopping criterion was promptly met, indicating efficient training. The confusion matrix highlights the model's perfect classification accuracy, achieving 100% accuracy in both the training and testing datasets. All instances of "No" and "Yes" were correctly predicted, with no false positives or false negatives. This flawless performance indicates that the model is highly effective at predicting the decision.

Table 13

Table 13. Area Under the Curve

		Area
2. credit decisions on past customer relationships rather than considering current creditworthiness	No	1.000
	Yes	1.000

Source: Calculations performed by the author using SPSS software.

The AUC values for both 'Yes' and 'No' responses for the dependent variable "credit decisions on past customer relationships rather than considering current creditworthiness" are 1.000. This theoretically indicates perfect classification performance by the model, meaning it should be able to perfectly distinguish between those who base credit decisions on past customer relationships and those who consider current creditworthiness, without any error.

9.3.4. SIGNIFICANT PREDICTORS

Table 14

Table 14 Independent Variable Importance

Predictors	Importance	Normalized Importance

2(a). reliance on familiar and trusted business relationships	.095	69.4%
2(b). simplify decision-making and reduce cognitive effort	.104	76.1%
2(c). maintain consistency in credit management practices	.089	64.8%
2(d). avoid the uncertainty	.087	63.7%
2(e). align with historical patterns	.137	100.0%
2(f). prioritize data-driven decision-making	.105	76.7%
2(g). ensure fairness and consistency	.118	86.4%
2(h). mitigate credit risk and protect cash flow	.098	71.4%
2(i). avoid biases and subjective judgments	.109	80.1%
2(j). foster a culture of continuous improvement	.059	43.4%

Source: Calculations performed by the author using SPSS software.

The analysis revealed that the variables "align with historical patterns" and "ensure fairness and consistency" were significant predictors of the outcome, with importance weights of 0.137 and 0.118, respectively. Additionally, "avoid biases and subjective judgments" (0.109) and "prioritize data-driven decision-making" (0.105) also emerged as notable predictors. These variables have the highest normalized importance scores, indicating their substantial impact on predicting credit decisions based on past customer relationships rather than considering current creditworthiness.

9.3.5. IMPLICATIONS

The findings suggest that relying on historical patterns and ensuring fairness and consistency are crucial factors influencing credit decisions based on past customer relationships. Emphasizing data-driven decision-making and avoiding biases can enhance credit management practices. These insights highlight the need for strategies that balance historical insights with current credit assessments to mitigate risks effectively.

9.4. HYPOTHESIS TESTING

Table 15

Table 15. Hypothesis Testing Results

Hypothesis	Result	Conclusion
H1: Representativeness bias significantly affects the accounts payables of entrepreneurs in the Golaghat District, leading to decisions that prioritize past relationships over current financial assessments.		Representativeness bias significantly influences accounts payables decisions among entrepreneurs.
H2: Representativeness bias significantly impacts the accounts receivables of entrepreneurs in the Golaghat District, resulting in credit decisions that favor historical customer relationships rather than current creditworthiness.	Supported (Significant at $p < 0.05$) & (100% Accuracy, AUC = 1)	Representativeness bias significantly affects accounts receivables decisions among entrepreneurs.

Source: prepared by the author based on analysis outcomes.

10. CONCLUSION

This study investigated the impact of representativeness bias on accounts payables and receivables among entrepreneurs in Golaghat District, Assam, utilizing a quantitative methodology involving structured questionnaires distributed to 367 entrepreneurs. The objectives were twofold: to examine how representativeness bias affects accounts payables, focusing on past experiences with suppliers, and to analyze its impact on accounts receivables, emphasizing historical customer relationships. The working hypotheses were formulated as follows: H1 posited that representativeness bias significantly affects accounts payables, while H2 suggested it significantly impacts accounts receivables. Hypothesis testing results supported both hypotheses, with H1 demonstrating significance at $p < 0.05$ and H2 achieving 100% accuracy and an AUC of 1, indicating effective modeling of the relationships involved.

The analysis revealed that entrepreneurs are inclined to prioritize past relationships over current financial assessments in their payment decisions and credit evaluations, thereby exposing themselves to potential financial risks. This research fills a notable gap in the literature concerning behavioral biases in entrepreneurial finance, particularly within the context of small and medium-sized enterprises (SMEs) in rural India. The findings underscore the necessity for entrepreneurs to integrate both historical and contemporary data in their decision-making processes to mitigate financial risks effectively. Overall, this study offers valuable insights into the cognitive biases influencing financial management practices, suggesting further exploration of various biases in similar contexts for future research.

CONFLICT OF INTERESTS

None .

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