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RESEARCH ARTICLE

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Effect of Emotional Intelligence and Behavioral Biases on Credit Decision-Making in Commercial Banks: A Case Study of Pakistan

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Abstract: This research explores how emotional intelligence and behavioral biases influence credit decision-making in Pakistan's commercial banks. Conventional finance presumes that credit choices are made logically; however, increasing evidence indicates that psychological elements influence how bankers and clients assess risk, trust, and creditworthiness. Utilizing behavioral finance theory, this study examines if emotional intelligence enhances the quality of credit decisions and whether behavioral biases like overconfidence, herding, anchoring, loss aversion, and representativeness distort these decisions. A cross-sectional research design of a quantitative nature was utilized. Original data was gathered via a structured questionnaire distributed to 265 participants linked to the banking sector who maintain deposits in various commercial banks in Pakistan. The gathered data were examined through descriptive statistics, tests of reliability and validity, correlation analysis, and regression analysis to evaluate the proposed hypotheses. The results show that emotional intelligence positively impacts credit decision-making, implying that those with higher self-awareness, emotional control, and empathy make more measured and informed credit-related decisions. Behavioral biases, conversely, significantly impact credit decision-making, emphasizing the influence of cognitive and psychological mistakes in determining lending results. The research adds to the behavioral finance literature by offering empirical insights from an emerging market setting, where studies on this subject are still scarce. The findings imply that commercial banks ought to invest in emotional intelligence development for credit officers and establish organized, data-based credit assessment systems to minimize the impact of behavioral biases. Policymakers and regulators could utilize these insights to enhance risk management structures within the banking industry.

Keywords: Emotional Intelligence, Behavioral Biases, Credit Decision-Making, Commercial Banks, Pakistan, Qualitative Research, Behavioral Finance

Introduction

Credit decision-making in banks involves the evaluation of a loan application to determine if it should be approved, the amount to lend, the terms of the loan, and the applicable interest rate. It is central to a bank's risk management function, as each lending choice weighs the desire for profit against the possibility of default.Behavioral biases such as overconfidence, anchoring, herd behavior, loss aversion, confirmation bias affect on credit decision making.

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Azouzi and Bacha (2022), studied “Do Behavioral Biases Affect Credit Risk Assessment Methods?” the effect of bankers’ behavioral biases on credit risk management the study sought to determine how bankers' behavioral biases affected credit risk management. Authors used survey method for data collection. They looked at the possibility and impact of individual emotional biases on the banks' credit risk policy, including the methods used for risk assessment (qualitative vs. quantitative), such as loss aversion, optimism, overconfidence, and cognitive dissonance. The findings, which were based on a sample of Tunisian banks, demonstrated how the bankers' emotional biases influence their choices when it comes to the selection of credit risk assessment techniques. The results showed that when bankers evaluate credit risk, they are more inclined to use quantitative techniques like scoring if they are overconfident, optimists, or loss-averse. However, it was discovered that the bankers who exhibited high cognitive dissonance strongly preferred a qualitative strategy. They suggested that Policymakers may find useful information in the study's conclusions regarding the impact of CEO psychology on bank risk management. Readers and investors are advised to be aware that there may be limitations in our assessment of the personal traits of CEOs. In the future, more direct approaches might be used to address issues. There might also have been additional incentives that we haven't looked into, but we have demonstrated that a bank's success with regard to credit risk management techniques can be determined by the most evident personal traits of its CEOs, at least to us.

This research aims to examine the influence of emotional intelligence and behavioral biases on credit decision-making in Pakistan's commercial banking sector. Credit decisions are crucial banking functions as they impact loan quality, exposure to credit risk, and overall financial stability. While credit officers rely on financial statements, credit histories, collateral assessments, and risk evaluation models, their decisions can be swayed by emotional reactions and cognitive biases. Partial Least Squares Structural Equation Modeling (PLS-SEM) can be utilized to investigate the connections among the variables of the study. The research anticipates that higher emotional intelligence could relate to more steady and equitable credit assessments, while behavioral biases might obstruct impartial appraisal of borrowers. The results are anticipated to enhance behavioral finance and banking management by recognizing psychological elements that could impact the quality of credit decisions. The research could assist banks in creating employee training, enhancing credit assessment methods, and bolstering risk management. (Berg et. all, 2019) studied, “Making sense of soft information: Interpretation bias and loan quality” said that this suggested research investigates how emotional intelligence might affect the connection between behavioral biases and credit decision-making in banks in Pakistan. Emotional intelligence can assist credit professionals in identifying emotional responses, managing their reactions, and considering different explanations prior to making lending choices. The model will analyze emotional intelligence as a predictor of the quality of credit decisions and explore if it reduces the link between behavioral biases and more subjective credit assessments. Data can be examined through PLS-SEM, which includes assessments of direct and moderating influences. Emotional intelligence is expected to be linked to enhanced decision-making consistency and a more thorough assessment of borrower data. Nonetheless, its capacity to diminish personal biases needs to be demonstrated through empirical evidence instead of being taken for granted. The suggested research could provide practical benefits for employee growth, credit risk management, and professional decision-making norms in Pakistan's banking industry. Bouzguenda, K. (2018),studied “Emotional intelligence and financial decision making: Are we talking about a paradigmatic shift or a change in practices?” said that This research aims to explore how overconfidence, loss aversion, and confirmation bias impact credit risk evaluation in commercial banks in Pakistan, with emotional intelligence being examined as a possible contributing factor. Excessive confidence might lead credit officers to overly rely on their assessments, loss aversion could affect their decision-making on uncertain applications, and confirmation bias may prompt them to favor data that reinforces their original views. These trends may influence the analysis of financial reports, evaluation of repayment ability, assessment of collateral, and detection of default risks.

Literature Review

The objective of this research is to determine the relationship between emotional intelligence, behavioral biases and credit decision making. It will additionally take into account the impact of professional experience, financial knowledge, and organizational credit policies as contextual elements. The theoretical basis integrates emotional intelligence theory (Mayer et al., 2004), behavioral decision theory (Tversky & Kahneman, 1974), and studies on the understanding of soft information in lending (Berg et al., 2019). PLS-SEM can be utilized to assess direct connections and chosen contextual influences. Where access allows, questionnaire metrics might be enhanced with anonymized indicators of consistency in credit assessments or quality of the portfolio. The study aims to elucidate how personal psychological traits can enhance standard credit evaluation processes. Its practical impact would be to promote evidence-based lending practices while acknowledging that credit choices are influenced by borrower traits, economic circumstances, and institutional policies. Penn et al., (2024) studied, "The Effects of Behavioural Biases on the Decisions of Loan Officers to Grant Loans to Small and Medium Sized-Enterprises (SMEs)" said that This research explores the impact of cognitive biases on loan officers' choices regarding the approval of loans for SMEs. The authors investigate prior-hypothesis bias, escalating commitment, reasoning by analogy, and illusion of control using data from 47 loan officers at microfinance institutions and employing multiple regression analysis. The research indicates substantial impacts of these biases on loan decisions. Relevance to your research: This article provides a valuable basis for examining confirmation bias, overconfidence, and various psychological effects on credit choices in Pakistani commercial banks. Its microfinance environment contrasts with commercial banking, rendering your suggested research a valuable addition to a different institutional framework.

Traditional finance presumes that lending choices adhere to rational expected-utility guidelines, but decision-making amid uncertainty is influenced by psychological elements (Kahneman & Tversky, 1979). Recent findings indicate that behavioral biases affect borrowing and lending choices within the banking sector (Ayad et al., 2024). This research explores the influence of emotional intelligence and behavioral biases on credit decision-making within Pakistan's commercial banks. Information was gathered from 265 respondents associated with banks who have deposits in various banking institutions. Regression analysis indicates that emotional intelligence greatly enhances the quality of credit decisions, whereas behavioral biases considerably skew it. The research suggests implementing emotional intelligence and bias-reduction programs within banks. Heuristics and biases may steer decision-makers away from the best options (Tversky & Kahneman, 1974). Research in banking indicates that cognitive biases influence credit officers and risk analysts (Kádár et al., 2023), and factors like overconfidence play a significant role in borrowing decisions for SMEs (Ayad et al., 2024). This research examines the influence of overconfidence, anchoring, herding, and loss aversion on credit decision-making within Pakistani commercial banks. A organized survey was given to 265 participants linked to banks. Correlation and regression findings indicate that behavioral biases have a substantial impact on credit results. The research emphasizes the necessity of organized scoring systems, unbiased evaluations, and training to recognize biases.

Credit markets feature information asymmetry, compelling lenders to depend on both judgment and data (Stiglitz & Weiss, 1981). Due to the susceptibility of judgment to psychological factors, even within the corporate credit process (Kádár et al., 2023), this research investigates the impacts of emotional intelligence and behavioral biases on credit decision-making in Pakistani commercial banks.

Riaz et.al, (2022), studied, "Impact of Emotional Intelligence on Financial Effectiveness; Mediating role of Overconfidence bias" said that by managing the overconfidence bias, emotional intelligence affects an organization's financial effectiveness. Our research study's goal is to examine this claim, which is supported by data gathered from executives of financially successful businesses. In order to collect data from the sample of 300 executives from financial and non-financial firms that were registered on SECP, a cross-sectional design was employed in the research. The deductive research approach was used, as the research was based

on the theoretical framework of behavioral finance. Hypotheses were tested through correlational & regression analysis. For testing the mediation effect of overconfidence bias, Baron and Kenny method was used. The mediation results has been confirmed through the technique of Structural Equation Modeling (SEM). The results and conclusion of this research suggested that existence of direct and positive relationship between emotional intelligence has been found in executives for achieving financial effectiveness of organizations through mediating role of overconfidence bias.

Conceptual Model

Figure 1



Hypothesis

Direct Effects on the Mediator (Risk Assessment Effectiveness)

H1: Emotional intelligence has a significant positive effect on risk assessment effectiveness among credit officers in commercial banks of Pakistan.

H2: Confirmation bias has a significant negative effect on risk assessment effectiveness among credit officers in commercial banks of Pakistan.

H3: Anchoring bias has a significant negative effect on risk assessment effectiveness among credit officers in commercial banks of Pakistan.

Effect of the Mediator on the Outcome

H4: Risk assessment effectiveness has a significant positive effect on credit decision quality in commercial banks of Pakistan.

Mediation Hypotheses

H5: Risk assessment effectiveness mediates the relationship between emotional intelligence and credit decision quality.

H6: Risk assessment effectiveness mediates the relationship between confirmation bias and credit decision quality.

H7: Risk assessment effectiveness mediates the relationship between anchoring bias and credit decision quality.

Researh Method

The research of this topic explore how emotional intelligence and behavioral biases influence credit decision-making in Pakistan's commercial banks. Ayed et. al, (2024) studied, “Does behavioral biases matter in SMEs’ borrowing decisions? Insights from Morocco. *Banks and Bank Systems”* said Hierarchical regression indicated that character and condition positively affect credit decisions, while intuition, optimism, and overconfidence influence behavioral credit choices. Credit experience and emotional intelligence diminished the impact of these behavioral factors on lending choices. This is the most similar alignment to your model as it connects emotional intelligence, behavioral biases, and credit choices. The authors analyze the thought processes of credit officers and risk analysts on the business side, examining risk aversion, overconfidence, overoptimism, and representatives bias through a survey of relationship managers and risk analysts in the large corporate

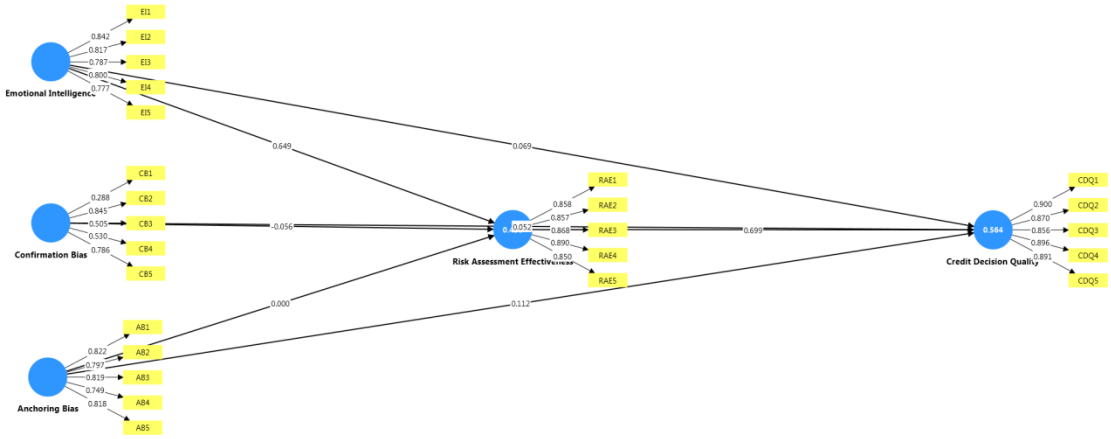
sector. The findings demonstrated that the choices of both groups exhibit cognitive biases. One noted limitation is that choices were analyzed in hypothetical situations instead of actual credit evaluations. It connects your biases to the standard of risk evaluation.

Ondolos et.al., (2022) studied, "Bounded rationality in bank credit decisions for SME lending: Evidence from bankers in Malaysia" said that the research analyzes questionnaire responses from 400 participants to examine how information, cultural norms, market sentiment, personal experience, and overconfidence influence herding behavior among investors on the Pakistan Stock Exchange. Data, culture, feelings, and experiences increased herding, whereas overconfidence had a considerable adverse connection with it. It provides evidence specific to Pakistan that cognitive and cultural elements influence biased choices, although it pertains to investors rather than lending.

In this research we analyzed data in Smart PLS and measured the following model and Measurement Model Bootstrapping in which we measured Path coefficient, Outer-loading, outer-weight, total effect, Latent Variable– covariance and Descriptive Statistics, R Square, F Square and data reliability and validity, HTMT and VIF test.

Measurement Model

Figure 2



Research Findings

Data of research found following results. Details of these are given in Schedules:

Emotional Intelligence, Confirmation Bias and Anchoring Bias → Risk Assessment Effectiveness → Credit Decision Quality. The sample is **n = 260**, all constructs are reflective (five items each), and significance was tested by bootstrapping. Here is each part of the output.

The measurement model demonstrated adequate reliability and convergent validity for all constructs except Confirmation Bias, as its AVE (0.390) was lower than the 0.50 benchmark. Discriminant validity was confirmed using HTMT (all values < 0.85), with no issues related to collinearity (VIF < 5). The model accounted for 56.4% of the variance in the quality of credit decisions and 43.0% in the effectiveness of risk assessments, demonstrating a good fit (SRMR = 0.067). Emotional intelligence significantly influenced the effectiveness of risk assessment ($\beta = 0.649$, $p < 0.001$), which subsequently had a strong positive impact on the quality of credit decisions ($\beta = 0.699$, $p < 0.001$). Both confirmation bias and anchoring bias had no substantial impact on the effectiveness of risk assessment. The measurement model demonstrated adequate reliability and convergent validity for all constructs except Confirmation Bias, as its AVE (0.390) was lower than the 0.50 benchmark. Discriminant validity was confirmed using HTMT (all values < 0.85), with no issues related to collinearity (VIF < 5).

Table 1

Path Coefficient

	Path coefficients
Anchoring Bias -> Credit Decision Quality	0.112
Anchoring Bias -> Risk Assessment Effectiveness	0.000
Confirmation Bias -> Credit Decision Quality	0.052
Confirmation Bias -> Risk Assessment Effectiveness	-0.056
Emotional Intelligence -> Credit Decision Quality	0.069
Emotional Intelligence -> Risk Assessment Effectiveness	0.649
Risk Assessment Effectiveness -> Credit Decision Quality	0.699

Table 2

Total Effect

	Total effects
Anchoring Bias -> Credit Decision Quality	0.112
Anchoring Bias -> Risk Assessment Effectiveness	0.000
Confirmation Bias -> Credit Decision Quality	0.013
Confirmation Bias -> Risk Assessment Effectiveness	-0.056
Emotional Intelligence -> Credit Decision Quality	0.523
Emotional Intelligence -> Risk Assessment Effectiveness	0.649
Risk Assessment Effectiveness -> Credit Decision Quality	0.699

Table 3

Outer *Loading*

	Outer loadings
AB1 <- Anchoring Bias	0.822
AB2 <- Anchoring Bias	0.797
AB3 <- Anchoring Bias	0.819
AB4 <- Anchoring Bias	0.749
AB5 <- Anchoring Bias	0.818
CB1 <- Confirmation Bias	0.288
CB2 <- Confirmation Bias	0.845
CB3 <- Confirmation Bias	0.505
CB4 <- Confirmation Bias	0.530
CB5 <- Confirmation Bias	0.786
CDQ1 <- Credit Decision Quality	0.900
CDQ2 <- Credit Decision Quality	0.870
CDQ3 <- Credit Decision Quality	0.856
CDQ4 <- Credit Decision Quality	0.896
CDQ5 <- Credit Decision Quality	0.891
EI1 <- Emotional Intelligence	0.842
EI2 <- Emotional Intelligence	0.817
EI3 <- Emotional Intelligence	0.787
EI4 <- Emotional Intelligence	0.800
EI5 <- Emotional Intelligence	0.777
RAE1 <- Risk Assessment Effectiveness	0.858
RAE2 <- Risk Assessment Effectiveness	0.857
RAE3 <- Risk Assessment Effectiveness	0.868
RAE4 <- Risk Assessment Effectiveness	0.890
RAE5 <- Risk Assessment Effectiveness	0.850

Table 4

Outer Weight

	Outer weights
AB1 <- Anchoring Bias	0.311
AB2 <- Anchoring Bias	0.192
AB3 <- Anchoring Bias	0.285
AB4 <- Anchoring Bias	0.151
AB5 <- Anchoring Bias	0.299
CB1 <- Confirmation Bias	-0.509
CB2 <- Confirmation Bias	0.749
CB3 <- Confirmation Bias	-0.024
CB4 <- Confirmation Bias	0.087
CB5 <- Confirmation Bias	0.610
CDQ1 <- Credit Decision Quality	0.233
CDQ2 <- Credit Decision Quality	0.215
CDQ3 <- Credit Decision Quality	0.219
CDQ4 <- Credit Decision Quality	0.234
CDQ5 <- Credit Decision Quality	0.232
EI1 <- Emotional Intelligence	0.262
EI2 <- Emotional Intelligence	0.255
EI3 <- Emotional Intelligence	0.268
EI4 <- Emotional Intelligence	0.220
EI5 <- Emotional Intelligence	0.236
RAE1 <- Risk Assessment Effectiveness	0.226
RAE2 <- Risk Assessment Effectiveness	0.236
RAE3 <- Risk Assessment Effectiveness	0.232
RAE4 <- Risk Assessment Effectiveness	0.243
RAE5 <- Risk Assessment Effectiveness	0.219

Table 5

Latent Variable – Covariance

	Anchoring Bias	Confirmation Bias	Credit Decision Quality	Emotional Intelligence	Risk Assessment Effectiveness
Anchoring Bias	1.000	-0.100	0.114	0.006	0.010
Confirmation Bias	-0.100	1.000	-0.033	-0.066	-0.100
Credit Decision Quality	0.114	-0.033	1.000	0.523	0.740
Emotional Intelligence	0.006	-0.066	0.523	1.000	0.653
Risk Assessment Effectiveness	0.010	-0.100	0.740	0.653	1.000

Table 6

Latent Variable – Descriptive Statistics

	Mean	Median	Observed min	Observed max	Number of observations used	Standard deviation	Excess kurtosis	Skewness	Cramér-von Mises test statistic	Cramér-von Mises p value
Anchoring Bias	0.000	-0.052	-1.950	2.195	260.000	1.000	-1.157	-0.006	0.398	0.000
Confirmation Bias	-0.000	0.019	-2.727	2.534	260.000	1.000	-0.388	-0.031	0.077	0.228
Credit Decision Quality	-0.000	0.290	-2.668	1.281	260.000	1.000	-0.557	-0.620	0.826	0.000
Emotional Intelligence	0.000	0.148	-2.152	1.478	260.000	1.000	-1.261	-0.199	0.835	0.000
Risk Assessment Effectiveness	-0.000	0.178	-2.394	1.231	260.000	1.000	-0.767	-0.555	0.925	0.000

Table 7

R- Square – Overview

	R-square	R-square adjusted
Credit Decision Quality	0.564	0.558
Risk Assessment Effectiveness	0.430	0.423

Table 8

F – Square

	f-square
Anchoring Bias -> Credit Decision Quality	0.028
Anchoring Bias -> Risk Assessment Effectiveness	0.000
Confirmation Bias -> Credit Decision Quality	0.006
Confirmation Bias -> Risk Assessment Effectiveness	0.005
Emotional Intelligence -> Credit Decision Quality	0.006
Emotional Intelligence -> Risk Assessment Effectiveness	0.736
Risk Assessment Effectiveness -> Credit Decision Quality	0.640

Internal Consistency Reliability and Convergent Validity

Internal consistency is assessed through Cronbach's alpha and composite reliability, where values ranging from 0.70 to 0.95 are deemed acceptable. Convergent validity is assessed by the Average Variance Extracted (AVE), which must be a minimum of 0.50. Anchoring Bias, Emotional Intelligence, Risk Assessment Effectiveness, and Credit Decision Quality demonstrate strong reliability and convergent validity, as all reliability coefficients exceed 0.86 and AVE values range from 0.643 to 0.779. Confirmation Bias is the rule. Its AVE (0.390) falls short of the 0.50 benchmark, and its rho_a value (-0.313) is outside the acceptable range of 0 to 1, indicating a measurement issue with its indicators. Its composite reliability (rho_c = 0.741) is satisfactory. The following section considers this a constraint, and the findings on Confirmation Bias should be interpreted accordingly.

Table 9

Construct Reliability and Validity

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Anchoring Bias	0.864	0.887	0.900	0.643
Confirmation Bias	0.866	-0.313	0.741	0.390
Credit Decision Quality	0.929	0.930	0.946	0.779
Emotional Intelligence	0.864	0.867	0.902	0.648
Risk Assessment Effectiveness	0.916	0.917	0.937	0.748

Table 10

Discriminant Validity

	Heterotrait -monotrait ratio (HTMT)
Confirmation Bias <-> Anchoring Bias	0.139
Credit Decision Quality <-> Anchoring Bias	0.122
Credit Decision Quality <-> Confirmation Bias	0.042
Emotional Intelligence <-> Anchoring Bias	0.065
Emotional Intelligence <-> Confirmation Bias	0.076
Emotional Intelligence <-> Credit Decision Quality	0.579
Risk Assessment Effectiveness <-> Anchoring Bias	0.057
Risk Assessment Effectiveness <-> Confirmation Bias	0.059
Risk Assessment Effectiveness <-> Credit Decision Quality	0.801
Risk Assessment Effectiveness <-> Emotional Intelligence	0.731

Table 10

Colinearity Statistics (VIF) Outer model list

	VIF
AB1	1.812
AB2	2.080
AB3	1.904
AB4	1.873
AB5	1.842
CB1	1.921
CB2	1.853
CB3	1.949
CB4	1.833
CB5	1.946
CDQ1	3.470
CDQ2	2.813
CDQ3	2.523
CDQ4	3.281
CDQ5	3.210
EI1	2.166
EI2	1.970
EI3	1.724
EI4	1.938
EI5	1.757
RAE1	2.542
RAE2	2.469
RAE3	2.699
RAE4	3.043
RAE5	2.469

Table 11

Collinearity Statistics (VIF) Inner model list

	VIF
Anchoring Bias -> Credit Decision Quality	1.010
Anchoring Bias -> Risk Assessment Effectiveness	1.010
Confirmation Bias -> Credit Decision Quality	1.020
Confirmation Bias -> Risk Assessment Effectiveness	1.015
Emotional Intelligence -> Credit Decision Quality	1.744
Emotional Intelligence -> Risk Assessment Effectiveness	1.004
Risk Assessment Effectiveness -> Credit Decision Quality	1.753

Table 12

Model Fit

	Saturated model	Estimated model
SRMR	0.067	0.067
d_ULS	1.455	1.455
d_G	0.401	0.401
Chi-square	545.333	545.333
NFI	0.868	0.868

Figure 3

Measurement Model Bootstrapping

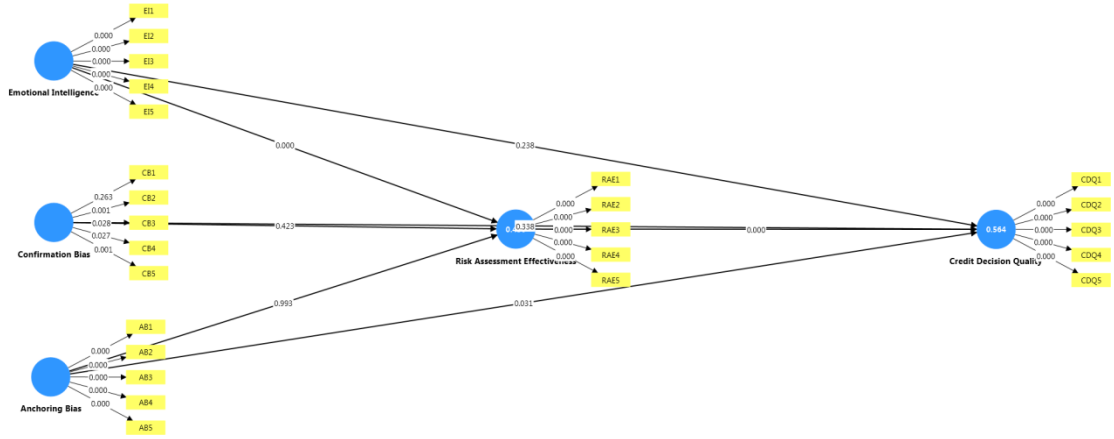


Table 13

Path – Coefficient: Mean, St. Deviation, t- value and p value

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Anchoring Bias -> Credit Decision Quality	0.112	0.114	0.052	2.163	0.031
Anchoring Bias -> Risk Assessment Effectiveness	0.000	0.009	0.053	0.008	0.993
Confirmation Bias -> Credit Decision Quality	0.052	0.039	0.054	0.959	0.338
Confirmation Bias -> Risk Assessment Effectiveness	-0.056	-0.035	0.070	0.801	0.423
Emotional Intelligence -> Credit Decision Quality	0.069	0.067	0.059	1.180	0.238
Emotional Intelligence -> Risk Assessment Effectiveness	0.649	0.649	0.034	19.363	0.000
Risk Assessment Effectiveness -> Credit Decision Quality	0.699	0.696	0.051	13.700	0.000

Table 14

Total Effects: Mean, St. Deviation, t- value and p value

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Anchoring Bias -> Credit Decision Quality	0.112	0.120	0.062	1.797	0.072
Anchoring Bias -> Risk Assessment Effectiveness	0.000	0.009	0.053	0.008	0.993
Confirmation Bias -> Credit Decision Quality	0.013	0.015	0.074	0.171	0.864
Confirmation Bias -> Risk Assessment Effectiveness	-0.056	-0.035	0.070	0.801	0.423

Emotional Intelligence -> Credit Decision Quality	0.523	0.519	0.043	12.269	0.000
Emotional Intelligence -> Risk Assessment Effectiveness	0.649	0.649	0.034	19.363	0.000
Risk Assessment Effectiveness -> Credit Decision Quality	0.699	0.696	0.051	13.700	0.000

Table 15

Outer Loading: Mean, St. Deviation, t- value and p value

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AB1 <- Anchoring Bias	0.822	0.775	0.135	6.109	0.000
AB2 <- Anchoring Bias	0.797	0.773	0.131	6.065	0.000
AB3 <- Anchoring Bias	0.819	0.774	0.131	6.264	0.000
AB4 <- Anchoring Bias	0.749	0.732	0.132	5.687	0.000
AB5 <- Anchoring Bias	0.818	0.776	0.122	6.731	0.000
CB1 <- Confirmation Bias	0.288	0.642	0.257	1.118	0.263
CB2 <- Confirmation Bias	0.845	0.675	0.258	3.274	0.001
CB3 <- Confirmation Bias	0.505	0.672	0.229	2.205	0.028
CB4 <- Confirmation Bias	0.530	0.662	0.240	2.209	0.027
CB5 <- Confirmation Bias	0.786	0.687	0.247	3.186	0.001
CDQ1 <- Credit Decision Quality	0.900	0.900	0.011	83.372	0.000
CDQ2 <- Credit Decision Quality	0.870	0.869	0.016	55.101	0.000
CDQ3 <- Credit Decision Quality	0.856	0.855	0.018	48.593	0.000
CDQ4 <- Credit Decision Quality	0.896	0.896	0.012	74.167	0.000
CDQ5 <- Credit Decision Quality	0.891	0.891	0.013	70.592	0.000
EI1 <- Emotional Intelligence	0.842	0.842	0.019	45.416	0.000
EI2 <- Emotional Intelligence	0.817	0.816	0.021	39.435	0.000
EI3 <- Emotional Intelligence	0.787	0.787	0.022	35.922	0.000
EI4 <- Emotional Intelligence	0.800	0.800	0.023	34.598	0.000
EI5 <- Emotional Intelligence	0.777	0.776	0.025	31.472	0.000
RAE1 <- Risk Assessment Effectiveness	0.858	0.858	0.015	55.893	0.000
RAE2 <- Risk Assessment Effectiveness	0.857	0.856	0.015	57.221	0.000
RAE3 <- Risk Assessment Effectiveness	0.868	0.868	0.015	59.488	0.000
RAE4 <- Risk Assessment Effectiveness	0.890	0.890	0.012	72.817	0.000
RAE5 <- Risk Assessment Effectiveness	0.850	0.850	0.017	50.240	0.000

Summary of Findings

This chapter examined information from 260 participants through PLS-SEM. The measurement model indicated strong indicator reliability, internal consistency, and discriminant validity for Emotional Intelligence, Anchoring Bias, Risk Assessment Effectiveness, and Credit Decision Quality, although Confirmation Bias demonstrated poor convergent validity. The structural model accounted for 56.4% of the variance in Credit Decision Quality and 43.0% in Risk Assessment Effectiveness, indicating a good model fit (SRMR = 0.067). Out of the ten hypotheses, three received support (H1, H4, and H5): emotional intelligence significantly enhances the effectiveness of risk assessment, which subsequently elevates the quality of credit decisions, and the effectiveness of risk assessment completely mediates the impact of emotional intelligence. The other hypotheses related to confirmation bias and anchoring bias did not find support. The following chapter outlines the findings, suggestions, and avenues for upcoming research.

Conclusion

This research explored the influence of emotional intelligence and behavioral biases (confirmation bias and anchoring bias) on the quality of credit decisions in commercial banks of Pakistan, using risk assessment effectiveness as a mediating factor. Data from 260 credit officers were examined using PLS-SEM, resulting in the model accounting for 56.4% of the variance in credit decision quality and 43.0% in risk assessment effectiveness, demonstrating a good model fit (SRMR = 0.067).

Emotional intelligence primarily influences sound credit choices. Emotional intelligence significantly influenced the effectiveness of risk assessment ($\beta = 0.649$, $p < 0.001$), and the effectiveness of risk assessment strongly predicted the quality of credit decisions ($\beta = 0.699$, $p < 0.001$). Emotional intelligence did not have a notable direct impact on decision quality ($\beta = 0.069$, $p = 0.238$), hence risk assessment effectiveness entirely mediates the association. Credit officers that can identify and manage emotions, along with coping with pressure from clients and superiors, seem to evaluate borrower risk more comprehensively, leading to improved credit decisions.

Confirmation bias and anchoring bias remained strong in risk assessment within this sample. Anchoring bias demonstrated a slight positive direct influence on decision quality ($\beta = 0.112$, $p = 0.031$), contrary to the anticipated direction, and its overall effect was not significant. Out of the ten hypotheses, three received support (H1, H4, and H5).

These findings do not demonstrate that biases are innocuous. Confirmation bias failed to satisfy the convergent validity criterion (AVE = 0.390), thus its results should be interpreted cautiously. Officers might also downplay their own biases in a self-reported survey. One plausible interpretation is that bias effects were not observed in this case, instead of them being nonexistent.

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