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BEHAVIORAL BIAS, ECONOMIC CONDITIONS, AND INFORMATION TECHNOLOGY: DETERMINANTS OF CREDIT ASSESSMENT IN INDONESIA

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ABSTRACT

Credit assessment plays a critical role in maintaining financial stability, particularly in emerging economies like Indonesia, where regional disparities in infrastructure and economic development make consistent credit evaluation difficult. Variability in institutional practices, the integration of information technology (IT), and behavioral biases among analysts contribute to inefficiencies and inaccuracies in credit decision-making. This study investigates the extent to which behavioral biases, economic conditions, and IT adoption influence credit assessment outcomes across Indonesian financial institutions. A cross-sectional online survey was conducted between April and October 2024, involving 454 credit analysts from commercial banks, rural banks, cooperatives, and non-bank financial institutions located in all central provinces of Indonesia. The study employs Partial Least Squares Structural Equation Modeling (PLS-SEM) to test both direct and moderating effects among the variables. The results show that economic conditions have a significant direct impact on credit assessment outcomes with an effect size of 0.486. Information technology also demonstrates a positive, though more negligible, direct effect, with an effect size of 0.137. Behavioral biases do not significantly influence credit assessment directly ($p = 0.759$), but their effect becomes significant when moderated by economic conditions (interaction effect = -0.217, $p < 0.001$). Information technology does not significantly moderate this relationship ($p = 0.885$). The findings indicate that the three predictors can explain 59.7% of the variance in credit assessment. These results emphasize the dominant role of economic context and technology over cognitive biases in determining credit evaluation outcomes across Indonesia's financial institutions.

INTRODUCTION

Credit assessment is a cornerstone of financial system stability and inclusive economic development. In developing economies such as Indonesia, where access to formal credit remains uneven, the reliability of credit evaluations holds critical implications for both financial institutions and underserved populations. The Indonesian financial system comprises a heterogeneous set of institutions, including commercial banks, rural banks, cooperatives, and non-bank financial institutions operating across regions with unequal levels of infrastructure, economic growth, and technological development. Despite regulatory efforts, disparities in credit risk assessment and high non-performing loan (NPL) ratios persist, raising concerns about inefficiencies in credit allocation (World Bank Group, 2022; Ridha et al., 2023; Baskara et al., 2016). Cognitive biases among credit analysts may further distort decision-making, particularly in uncertain or economically stressed environments (Hamid, 2025; Farooq et al., 2022; Baker et al., 2018).

The problem is exacerbated by uneven adoption of information technology (IT) and algorithmic tools, which, while capable of enhancing speed and consistency, may not eliminate human Bias, especially in cases requiring qualitative judgment (Branzoli et al., 2024; Addy et al., 2024). Scholars have noted that AI-assisted credit scoring often replicates

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historical Bias unless closely monitored (Kisten & Khosa, 2024; Umeaduma & Adedapo, 2025). At the same time, economic conditions directly influence lending behavior by shaping analysts' perceptions of risk and borrower quality (Makfiroh & Annisa, 2022; Basile et al., 2024). However, few studies offer an integrated empirical examination of how behavioral Bias, IT adoption, and economic context interact to shape credit assessment outcomes in emerging economies, particularly in Indonesia.

This study addresses the scientific problem of determining to what extent cognitive, technological, and contextual variables influence credit assessment quality, and how their interactions may amplify or mitigate systematic risk. Through a cross-sectional survey of 454 credit analysts and the application of Partial Least Squares Structural Equation Modeling (PLS-SEM), this research quantifies direct and moderating effects of behavioral Bias, economic conditions, and IT on credit decision-making in Indonesia's fragmented financial ecosystem (Hair et al., 2019; Hayes, 2022). The study's design captures institutional and geographic heterogeneity, offering insight into the robustness of credit assessment mechanisms under varying conditions.

The objective of this study is to analyze the influence of behavioral biases, economic conditions, and information technology on credit assessments in Indonesia, and to test the moderating effects of IT and economic context on the Bias–credit relationship. The paper is structured as follows: Section 2 presents the theoretical framework; Section 3 outlines the methodology and sample; Section 4 reports and interprets results; Section 5 discusses key findings; and Section 6 concludes with implications and future research directions.

LITERATURE REVIEW

Behavioral finance theory suggests that cognitive limitations, emotions, and mental shortcuts (heuristics) significantly affect financial decisions, including credit evaluation (Kahneman & Tversky, 1979). Credit analysts, like investors, are susceptible to overconfidence, availability bias, and anchoring, which may compromise objectivity in assessing borrower risk (Shefrin & Statman, 2000; Thaler, 2005).

Understanding credit assessment requires an interdisciplinary approach that incorporates behavioral finance, information technology (IT), and macroeconomic analysis. In emerging economies like Indonesia, systemic financial risks are influenced by how credit institutions process borrower information, often under conditions of uncertainty, incomplete data, and varying technological capacity. The theoretical foundations of this study lie at the intersection of decision theory, behavioral economics, and risk modeling under contextual constraints.

Credit assessment has evolved from traditional expert-based models into more complex algorithmic systems that blend quantitative scoring with qualitative judgment. Several scholars have emphasized the role of cognitive framing and institutional settings in shaping credit decisions (Baker et al., 2018; Zhang et al., 2019). These decisions are increasingly influenced by AI-based systems, which promise standardization but are often limited by Bias in historical data and uneven technological implementation (Addy et al., 2024; Umeaduma & Adedapo, 2025; Heaven, 2022). While advanced IT systems can enhance objectivity, they are only as reliable as their inputs and oversight frameworks (Kisten & Khosa, 2024). Moreover, Sadok et al. (2022) argue that while AI models improve scoring efficiency, they introduce new challenges related to ethical transparency and operational stability in credit evaluation contexts.

Behavioral finance explains that credit analysts are prone to systematic biases such as overconfidence, confirmation bias, and anchoring. These cognitive distortions become especially pronounced in environments of high uncertainty or limited data, which are common in many Indonesian provinces (Hamid, 2025; Farooq et al., 2022). Scholars argue that even with standardized tools, subjective judgment persists due to institutional culture and localized practices (Brotcke, 2022; Edunjobi & Odejide, 2024). Nwaimo et al. (2024) further emphasize that predictive analytics must be integrated with behavioral understanding to ensure that machine learning models do not systematically exclude underbanked populations.

Macroeconomic conditions further complicate credit evaluation. Regional economic instability, infrastructure gaps, and market asymmetry affect the risk assessment landscape and may prompt analysts to adopt more risk-averse or heuristics-based approaches (Makfiroh & Annisa, 2022; Altdorfer et al., 2024; Ridha et al., 2023). Empirical studies show that loan performance, credit approval standards, and scoring thresholds are strongly tied to economic indicators such as GDP growth, NPL ratios, and inflation trends (Basile et al., 2024; World Bank Group, 2022; Usyk, 2020).

Interactivity among these factors, behavioral, technological, and contextual, is central to understanding real-world credit assessment dynamics. For instance, Mhlanga (2021) notes that stress conditions may amplify biases even when IT is employed. This is corroborated by De Lange et al. (2022) and Hurlin et al. (2024) who argue that technological solutions alone are insufficient unless accompanied by institutional governance and fairness controls. Transparency and algorithmic Bias remain concerns, as discussed by da Silva and Soares (2023), who highlight the risks of automation bias and reduced human oversight in algorithmic credit scoring environments.

Moreover, recent contributions emphasize that AI models embedded in credit decisions must account for social equity, explainability, and regulatory alignment (Paravisini & Schoar, 2013; Klein, 2020). In Indonesian contexts, the uneven digitization and institutional fragmentation make these issues particularly salient (Putra, 2018). These insights highlight the need to empirically test the combined and moderating effects of behavioral Bias, economic conditions, and IT systems.

In summary, prior literature establishes that cognitive Bias, macroeconomic asymmetry, and technology each influence credit evaluation, but the joint impact and interplay among these factors remain empirically underexplored in the Indonesian context. This gap justifies the need for an integrated analysis grounded in a robust quantitative model.

Therefore, this study aims to analyze the influence of behavioral biases, economic conditions, and information technology on credit assessment practices in Indonesia's financial institutions and to assess whether economic and technological factors moderate the impact of behavioral biases. The main hypotheses are as follows:

H$_1$: Behavioral biases significantly influence credit assessment outcomes.
H$_2$: Economic conditions significantly influence credit assessment outcomes.
H$_3$: Information technology significantly influences credit assessment outcomes.
H$_4$: Economic conditions moderate the relationship between behavioral biases and credit assessment outcomes.
H$_5$: Information technology moderates the relationship between behavioral biases and credit assessment outcomes.

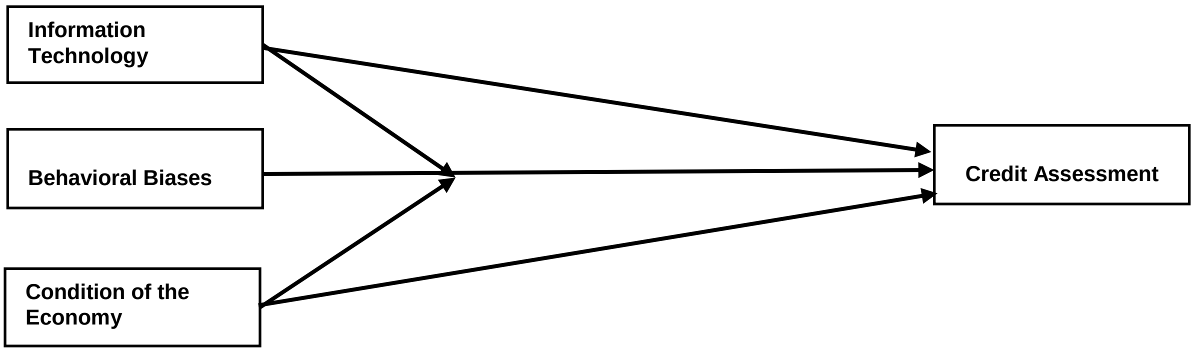

Figure 1. Theoretical Framework

MATERIALS AND METHODS

This study employed a quantitative, survey-based research design to investigate the influence of behavioral biases, economic conditions, and information technology on credit assessment outcomes in Indonesia. The procedure consisted of the following steps: (1) identifying eligible participants across financial institutions, (2) designing the survey instrument based on validated measures from prior research, (3) distributing the survey online, (4) collecting responses and performing data cleaning, and (5) analyzing the data using Partial Least Squares Structural Equation Modeling (PLS-SEM) to examine direct and moderating relationships.

The survey instrument was adapted from validated questionnaires used in previous studies (Baker et al., 2018; Pompian, 2021) and covered behavioral biases, economic conditions, IT adoption, and credit assessment outcomes. Items were measured primarily using a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). Questions were carefully selected to capture the most relevant dimensions affecting credit decisions while keeping the survey concise to encourage high response rates.

The complete questionnaire is available in the university repository, and a digital copy has been uploaded to https://dosen.unsurya.ac.id/repository/Saur_Costanius_Simamora_SP_MM_155924_Questionnaire_English.docx for public access.

Participation was voluntary, and all respondents provided informed consent prior to completing the survey. Responses were collected anonymously, and no personally identifiable information was retained. Measures were taken to minimize Bias, including random distribution of the survey and clear instructions emphasizing honest responses. The study protocol received ethical approval from the Faculty of Economic and Business Education, Universitas Pendidikan Indonesia (Approval No. B-1724/UN40.A7/PT.05/2025).

The survey was conducted between April and October 2024, distributed online to ensure accessibility across Indonesia's provinces. This period was chosen to capture current practices while allowing sufficient time for responses from geographically dispersed institutions. Data were analyzed using PLS-SEM, which is suitable for exploratory research with complex models and small-to-moderate sample sizes (Hair et al., 2019). Both the measurement and structural models were evaluated, including factor loadings, composite reliability (CR), Cronbach's alpha, average variance extracted (AVE), discriminant validity, and model fit indices. Bootstrapping with 454 resamples was employed to estimate the stability of path coefficients and validate hypotheses (Amaro et al., 2015; Straub et al., 2004). As shown in Figure 1, PLS-SEM was particularly appropriate because it allows simultaneous assessment of the measurement and structural models, aligning with the study's aim to investigate the direct and moderating roles of behavioral biases, economic conditions, and information technology in credit assessment outcomes. Behavioral Biases (BB) affect Credit Assessment (CA). IT and EC exert direct effects on CA. Two interactions—BB×IT and BB×EC—capture, respectively, IT is dampening and economic stress's amplifying roles on the BB→CA.

Guided by this model, we deploy a cross-sectional survey of Indonesian credit analysts and estimate a PLS-SEM to assess measurement validity and structural paths, including moderations. The design accommodates complex models and non-normal data, and we evaluate loadings, CR, AVE, and discriminant validity before hypothesis testing via bootstrapping. Sampling across provinces and institution types captures the heterogeneity necessary to identify moderation by IT and economic conditions (Hair et al., 2019).

The use of a structured survey instrument along with PLS-SEM analysis provided methodological rigor and strong verification of the collected data. Additionally, the wide geographic range of the sample enhances the generalizability of the findings, enabling an understanding of credit analysts' behavioral biases across Indonesia's diverse economic and institutional environments. Several validity and reliability assessments were conducted to ensure the survey instrument's rigor. The analysis of factor loadings indicated that all indicator variables exceeded the 0.6 threshold, indicating strong measurement of the constructs. The results indicate that Composite Reliability (CR) and Cronbach's alpha greater than 0.7 validate adequate internal consistency for all constructs, and that Average Variance Extracted (AVE) values were over 0.5, ensuring that the constructs had adequate explained variance from the so-called indicators. Discriminant validity was also evaluated using the Fornell-Larcker criterion, and it was confirmed that each construct was statistically distinguishable from other constructs, significantly reducing the risk of multicollinearity. To improve reliability, Sarstedt et al. (2021) recommended using a bootstrapping technique, which we implemented with 454 resamples. Owing to the exploratory nature of the study, PLS-SEM was deemed highly appropriate for model analysis and hypothesis testing. Consistent with previous study recommendations for testing causal hypotheses, we use a 454 bootstrap sample (Hayes, 2022). This approach provides estimates of factor loadings for individual items, indicators, and constructs, with CIs that allow evaluation of factor stability. To enhance the robustness of the results, bootstrapping was employed to assess the stability of the findings, providing further support for the validity of the study's conclusion.

RESULTS

A total of 454 credit analysts participated in this study, drawn from commercial banks, rural banks, cooperatives, and non-bank financial institutions across all central Indonesian provinces. The respondents represented credit analysts and loan officers from various institutions, including commercial banks, regional banks, cooperatives, and fintech lenders in Indonesia. Table 1 illustrates the distribution of respondents by gender and position. The majority (54%) of respondents were female, with the most common age group being 22-27 years. Most held a bachelor's degree and had 2 to 5 years of experience in credit-related functions.

Table 1. Participants Characteristics

Characteristic	Frequency	Percentage
Gender: Male	210	46.3%
Gender: Female	244	53.7%
Age : 22 – 27 yo	223	49.12%
Age : 28 – 43 yo	203	44.71%
Age : 44 - 59 yo	28	6.17%
Education: Diploma	45	9.9%
Education: Bachelor’s	320	70.5%
Education: Master’s	89	19.6%
Experience 2–5 years	203	44.7%
Experience 6–10 years	145	32.0%
Experience 11–15 years	106	23.3%

Source: Data Processed (2025)

Figure 2 presents the geographical distribution of the institutions. The highest response rates came from West Java (20.0%), Central Java (14.4%), and East Java (14.4%). Figure 3 shows the types of financial institutions, with commercial banks accounting for 39.9%, cooperatives 9.9%, and fintech companies 10.1%.

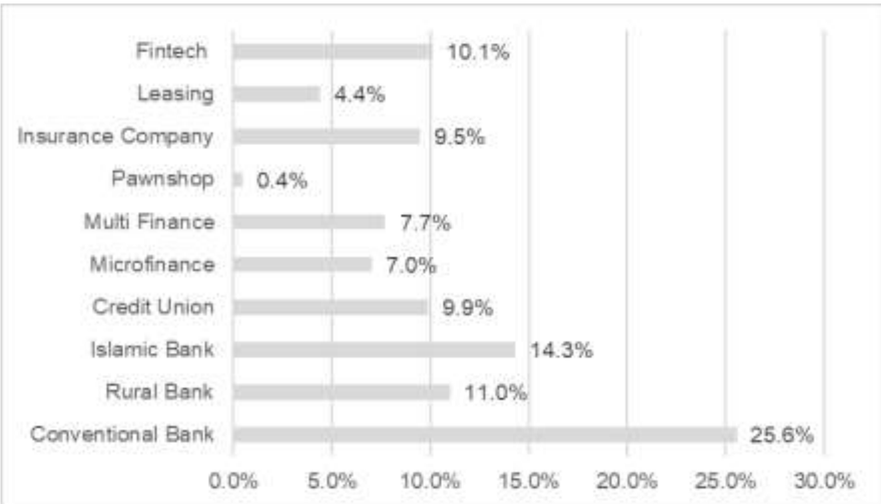

Figure 2. Type of Financial Institutions

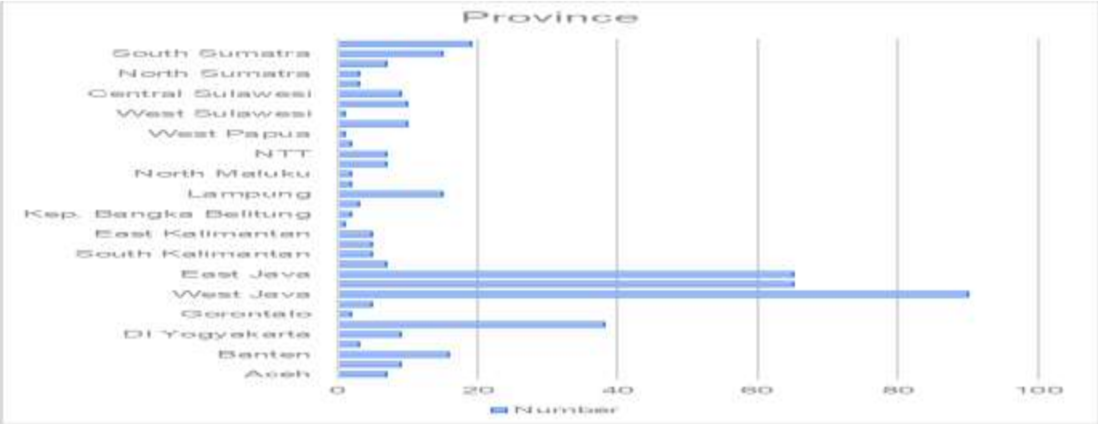

Figure 3. Credit Analyst Across Provinces

Figure 4 illustrates the types of lending process used: digital (34%), hybrid (45%), and traditional/manual (21%).

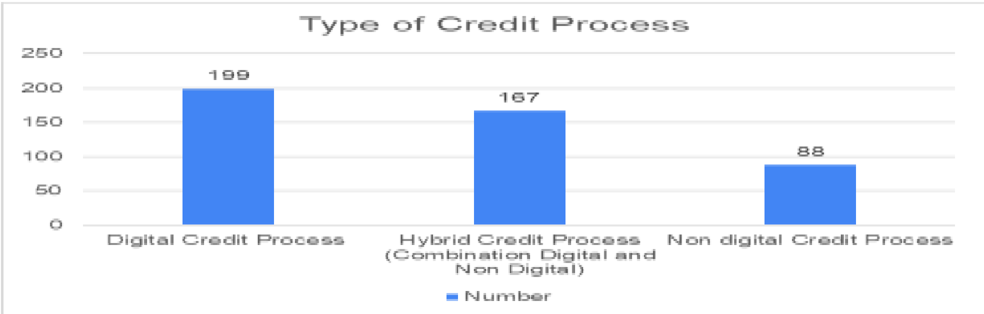

Figure 4. Type of Credit Process in Indonesia

To assess the reliability and validity of the constructs, outer loadings, Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE) were analyzed. Table 2 summarizes the values.

Table 2. Outer Loading, Construct Reliability, and Average Variance Extracted (AVE)

Construct	Item	Outer Loading	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
Behavioral Biases (BB)	BB6	0.770	0.949	0.955	0.954	0.578
	BB7	0.773				
	BB8	0.715				
	BB9	0.816				
	BB14	0.721				
	BB16	0.797				
	BB17	0.787				
	BB18	0.768				
	BB22	0.752				
	BB24	0.746				
	BB25	0.796				
	BB28	0.710				
	BB30	0.724				
	BB32	0.748				
	BB33	0.770				
Credit Assessment (CA)	CA2	0.779	0.687	0.695	0.810	0.517
	CA3	0.663				
	CA5	0.743				
	CA6	0.684				
Economic Condition (EC)	EC1	0.750	0.771	0.777	0.845	0.523
	EC2	0.760				
	EC3	0.620				
	EC5	0.753				
	EC6	0.723				
Information Technology (IT)	IT1	0.758	0.627	0.628	0.801	0.573
	IT2	0.738				
	IT3	0.774				

Source: Processed Data Results

Table 3. Discriminant Validity Analysis (Fornell-Larcker Criterion)

	BB	CA	EC	IT	CA*IT	CA*EC
BB	0.760					
CA	0.261	0.719				
EC	0.356	0.732	0.723			
IT	0.220	0.534	0.537	0.757		
CA*IT	-0.135	-0.522	-0.531	-0.613	0.701	
CA*EC	-0.19	-0.649	-0.665	-0.516	0.681	0.684

Source: Processed Data Results

The R^2 for the Credit Assessment construct is 0.597, indicating that the model explains 59.7% of the variance. Table 3 presents the effect size (f^2), and Table 4 presents the R^2.

Table 4. R-Square Test

	R-square	R-square adjusted
Credit Assessment	0.597	0.592

Source: Processed Data Results

Table 5. F-Square Test

Items	f-square
Behavioral Bias -> Credit Assessment	0.000
Condition of Economic -> Credit Assessment	0.272
Information Technology -> Credit Assessment	0.026
Condition of Economic x Behavioral Bias -> Credit Assessment	0.000
Information Technology x Behavioral Bias -> Credit Assessment	0.061

Source: Processed Data Results

Table 6 presents the standardized root mean square residual (SRMR), which was 0.071, below the 0.08 threshold, indicating a good model fit. NFI was 0.926.

Table 6. Model Fit

Items	Saturated Model	Estimated Model
SRMR	0.074	0.073
d_ULS	2.055	2.020
d_G	0.708	0.705
Chi-Square	1.848.583	1.833.672
NFI	0.744	0.746

Source: Processed Data Results

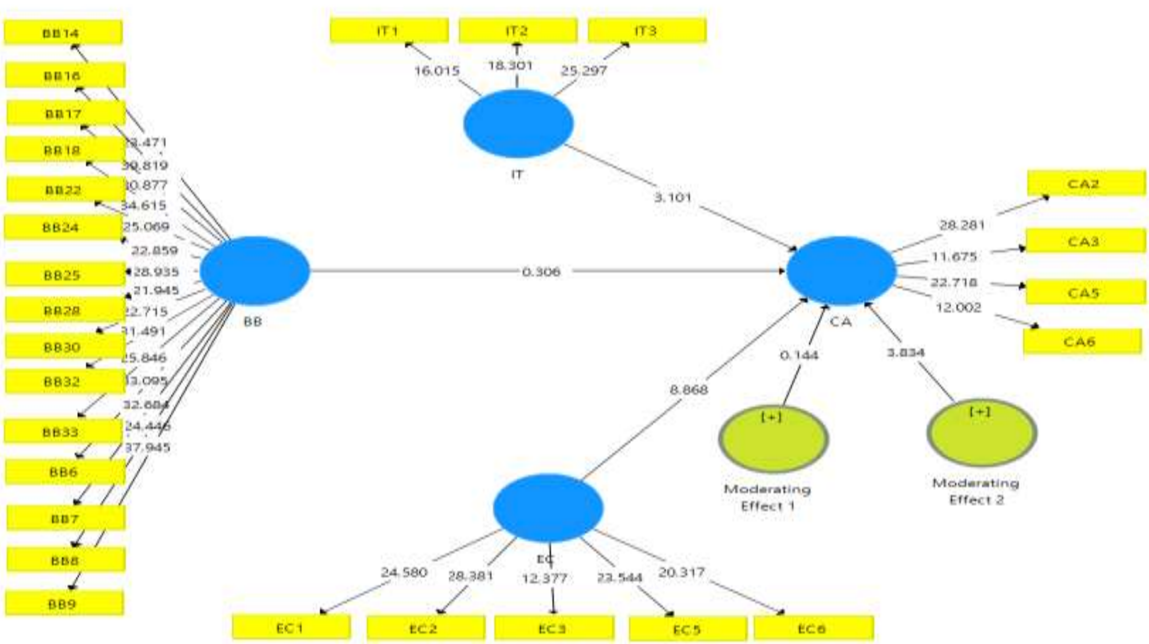

Figure 5. Result Model Diagram Bootstrapping

Table 7. Hypothesis Testing

Items	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	Decision
BB -> CA	0.010	0.016	0.031	0.306	0.759	Rejected
EC -> CA	0.486	0.478	0.055	8.868	0.000	Accepted
IT -> CA	0.137	0.134	0.044	3.101	0.002	Accepted
Moderating Effect 1 -> CA	-0.009	-0.01	0.064	0.144	0.885	Rejected
Moderating Effect 2 -> CA	-0.217	-0.223	0.057	3.834	0.000	Accepted

Source: Processed Data Results

DISCUSSIONS

A total of 454 credit analysts participated in the study, representing commercial banks, rural banks, cooperatives, and fintech lenders across all central provinces of Indonesia. Most respondents (53.7%) were female, and the dominant age group was 22–27 years (49.1%), indicating a relatively young demographic actively engaged in credit risk evaluation roles. This demographic distribution aligns with the emerging trend of younger professionals entering digital-based finance sectors. Educationally, a majority (70.5%) held a bachelor's degree, and 44.7% had 2–5 years of experience in credit-related roles. This early-career cohort suggests that credit assessment in Indonesia is increasingly being conducted by a new generation of analysts, potentially more open to structured frameworks and digital tools.

Regionally, the most significant number of participants came from West Java, Central Java, and East Java, reflecting the concentration of financial activity on Java Island. Regarding institutional type, commercial banks comprised the majority (39.9%), followed by fintech (10.1%) and cooperatives (9.9%). This mix reflects Indonesia's diverse financial ecosystem. In terms of the lending process, hybrid methods (manual + digital) dominated at 45%, while fully digital systems accounted for 34%. This further supports the idea that digital transformation in credit operations is underway, but still uneven.

The empirical findings show mixed support for the proposed hypotheses. Hypothesis H_1 is not supported, as behavioral biases (BB) were found to have no significant direct effect on credit assessment outcomes ($p = 0.759$). In contrast, H_2 and H_3 are supported, with economic conditions (EC) and information technology (IT) showing significant direct effects on credit assessment ($p < 0.001$ and $p = 0.002$, respectively). Regarding moderation effects, H_4 is supported, as EC significantly moderates the relationship between BB and credit assessment ($p < 0.001$), whereas H_5 is not supported, indicating that IT does not moderate this relationship ($p = 0.885$).

The finding that behavioral biases do not significantly affect credit decisions directly aligns with studies such as Azouzi and Bacha (2023) and Angelo et al. (2018), which emphasize that structured risk models and institutional safeguards can suppress individual Bias. In Indonesia, especially in the formal banking sectors, standardized scoring systems may override personal heuristics.

However, the moderating effect of economic conditions is reinforced (Farooq et al., 2022; Tanjung, 2023), who noted that under adverse economic conditions, cognitive biases tend to resurface due to heightened uncertainty. Economic conditions emerged as the most influential factor, consistent with Makfiroh and Annisa (2022) and Baskara et al. (2016), who found that macroeconomic variables such as GDP and inflation heavily influence lending behavior. Analysts in regions with economic instability tend to rely more on caution, leading to conservative credit assessments.

IT is positive, but a more negligible effect suggests its growing role in standardizing assessments, echoing the literature by Litty (2024) and Addy et al. (2024), which noted the advantages of AI-powered models in improving objectivity. However, IT's failure to moderate the BB→CA relationship highlights limitations in current technological adoption, particularly in Indonesia's non-uniform financial landscape, as noted by Kisten and Khosa (2024), who warn of an overreliance on algorithms without oversight.

This study enriches the behavioral finance and credit risk literature by providing an integrated framework that empirically validates interactions among psychological, technological, and macroeconomic variables. Prior works tended to isolate these factors; our results bridge that gap and validate context-dependent bias theories. The findings endorse a context-dependent model of credit bias, particularly relevant to emerging markets.

From a managerial perspective, the results indicate that digital tools alone are insufficient; institutional context and economic conditions remain critical. Adaptive credit scoring systems must be tailored not just to institutional typology but also to regional economic realities. Regulatory frameworks must ensure fairness and transparency in algorithmic decision-making, especially when human oversight remains necessary.

CONCLUSIONS

This study aimed to examine the influence of behavioral Bias, economic conditions, and information technology on credit assessment practices in Indonesia, including the moderating effects of economic conditions and IT. The results demonstrate that economic conditions and information technology significantly impact credit assessment decisions, while behavioral Bias alone does not exhibit a significant direct effect. However, when moderated by economic conditions, behavioral Bias exerts a significant influence, suggesting that cognitive distortions intensify during periods of macroeconomic uncertainty. The interaction between behavioral Bias and information technology was found to be statistically insignificant.

From these findings, credit assessments are shaped not only by rational-economic indicators but also by contextual and cognitive factors, especially in emerging economies. The role of economic stability remains paramount in credit evaluation, while digital systems, though supportive, are insufficient to eliminate human Bias.

This study makes a unique contribution by integrating behavioral finance theory, digital transformation, and macroeconomic considerations into a single predictive model, particularly in the Indonesian context. Such integration offers a broader lens through which analysts and institutions can evaluate credit risk.

Theoretically, the research supports the view that contextual moderators, especially macroeconomic environments, can influence the strength of cognitive bias effects. From a managerial perspective, it highlights the need for adaptive credit risk models that balance technological tools with human oversight. Institutions are encouraged to invest in both digital infrastructures and analyst training to mitigate risk effectively.

Limitations of this study include its cross-sectional design, which limits causal inference, and its focus on a single country, which may limit generalizability. Future research could adopt a longitudinal approach, conduct cross-country comparisons, or incorporate qualitative insights to capture nuances of decision-making.

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Conflicts of Interest: The authors declare no conflict of interest.

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