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Macroeconomic volatility and the value of AI analytics in Nigerian digital lending

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Abstract	Artificial intelligence can help digital lenders assess borrowers, but its value for credit risk management may vary with economic conditions. This study examines whether perceived macroeconomic volatility weakens the relationship between AI-driven predictive analytics and credit risk management performance in Nigeria. Drawing on contingency theory, it analyses survey responses from 185 digital lending professionals in Lagos State using partial least squares structural equation modelling with 5,000 bootstrap resamples. AI analytics was positively associated with perceived performance ($\beta = 0.382$, $p < 0.001$), while its interaction with macroeconomic volatility was negative and statistically significant ($\beta = -0.163$, $p = 0.006$; $f^2 = 0.063$). Alternative data utilization and regulatory compliance also showed positive associations with performance. Together, the predictors explained 68.4 percent of the variance in the outcome. The findings suggest that the relationship between analytics and risk management performance becomes weaker as perceived economic instability increases. They support a contingency perspective in which the benefits of technology depend partly on its operating environment. For digital lenders, the findings highlight the importance of model validation, borrower affordability and timely adjustments to lending policy.
Keywords	Artificial intelligence; digital lending; macroeconomic volatility; credit risk management; contingency theory; Nigeria

1. Introduction

Digital lenders use artificial intelligence to assess borrowers, process applications and monitor credit risk. Machine learning and alternative data allow lenders to examine information beyond conventional credit records, offering additional ways to assess borrowers with limited credit histories (Jagtiani & Lemieux, 2019). Their usefulness, however, also depends on the conditions under which lending decisions are made and loans are repaid. When the relationship between historical information and future outcomes changes, predictive models may require adjustment to remain useful (Gama et al., 2014). Understanding the value of AI in lending therefore requires attention to both analytical capability and the economic environment.

Existing research demonstrates the potential of advanced analytics in credit assessment. Using evidence from LendingClub, Jagtiani and Lemieux (2019) show how machine learning and alternative data extend borrower assessment beyond traditional information. Gambacorta et al. (2019) find that a model combining machine learning with nontraditional data predicts losses and defaults more effectively than traditional models during an adverse credit supply shock in China.

These findings suggest that AI can retain an advantage under difficult conditions. They also raise a broader question about how that advantage translates into organizational credit risk management performance.

Predictive accuracy and organizational performance are related, but they measure different aspects of lending. The comparative forecasting advantage examined by Gambacorta et al. (2019) concerns how effectively model predict losses and defaults. Organizational credit risk management also involves lending policy, borrower monitoring and recovery. A model may identify relatively safer borrowers while the lender still faces deteriorating repayment conditions across its portfolio. The implication is that stronger prediction alone may not establish whether the relationship between analytics and wider risk management outcomes remains equally strong during economic instability.

Nigeria provides a relevant setting for examining this relationship. The International Monetary Fund's 2025 Article IV assessment identifies persistent inflation and exposure to external uncertainty alongside reforms intended to strengthen economic stability (International Monetary Fund [IMF], 2025). Such pressures can affect household purchasing power and business conditions, creating challenges for lenders assessing repayment capacity. They also make it important to examine whether information drawn from borrowers' earlier financial behaviour remains useful as circumstances change. The concept drift literature provides a basis for this concern by showing how relationships between predictive inputs and outcomes can change over time (Gama et al., 2014).

The research gap addressed here lies between evidence on predictive performance and evidence on organizational lending outcomes. Jagtiani and Lemieux (2019) examine the informational contribution of alternative data and machine learning, while Gambacorta et al. (2019) assess comparative prediction under a credit supply shock. These studies do not directly establish whether perceived macroeconomic volatility weakens the relationship between AI analytics and broader credit risk management performance among Nigerian digital lenders. The distinction matters because an analytical advantage may persist even when its association with portfolio outcomes becomes weaker.

This study therefore examines whether perceived macroeconomic volatility moderates the relationship between AI-driven predictive analytics and credit risk management performance among digital lending professionals in Lagos State. Alternative data utilization and regulatory compliance are included to account for their accompanying relationships with performance. Contingency theory provides the theoretical foundation by relating organizational effectiveness to the fit between internal arrangements and environmental conditions (Donaldson, 2001). Applied here, it suggests that the value associated with analytics may vary with the economic pressures confronting lenders and borrowers.

The study contributes evidence on an environmental condition that may qualify the value of analytics in an emerging market lending setting. Its findings concern professionals' assessments of organizational practices and performance, rather than observed changes in algorithmic accuracy or realized loan losses. Although the evidence comes from one national setting, the relationship examined provides a basis for comparative research across markets with different economic exposures and institutional conditions.

2 Theory and hypothesis development

2.1 AI analytics as an organizational capability

AI-driven predictive analytics refers to the use of machine learning and related techniques to assess borrower risk, support credit decisions and monitor repayment behaviour. Its organizational value depends on how lenders combine analytical tools with data, professional expertise and decision processes. Gupta and George (2016) make this distinction in their study of big data analytics capability, showing that capability rests on a combination of organizational resources rather than technology investment alone. Their findings support examining analytics as part of an organization's operations, although they do not establish its effectiveness in digital lending specifically.

This distinction is important for credit risk management. A lender may produce accurate risk scores but make limited use of them when setting loan amounts, reviewing affordability or responding to repayment difficulties. Conversely, effective monitoring and recovery may improve portfolio outcomes even where scoring technology is relatively modest. The relationship examined in this study therefore concerns the organizational use of AI analytics and perceived credit risk management performance. It does not treat model accuracy as a substitute for the broader effectiveness of lending decisions.

Alternative data utilization and regulatory compliance are included as accompanying predictors. Additional borrower information may support assessment, while compliance practices concern the governance arrangements within which lending decisions are made. Including these variables allows the analytics–volatility relationship to be examined alongside other features of the lending process. Their inclusion does not imply that all competing explanations have been controlled.

2.2 Contingency theory and the economic environment

Contingency theory provides the principal explanation for the proposed moderation. Donaldson (2001) relates organizational effectiveness to the fit between internal arrangements and the conditions in which an organization operates. Applied to digital lending, this perspective suggests that the relationship between analytics and performance may vary as the economic circumstances of borrowers change.

The argument concerns the continuing fit between information, decisions and repayment conditions. A borrower's previous transactions may provide useful evidence of financial discipline and income regularity. Their relevance can nevertheless change when rising costs reduce disposable income or disrupt business cash flows. Under these circumstances, maintaining an analytical capability may be insufficient unless its outputs remain useful for current lending decisions. The proposed interaction captures this possibility: the association between analytics and performance may become weaker at higher levels of perceived economic instability.

Contingency theory does not require the relationship to weaken in every setting. A lender whose data and decision processes remain responsive may preserve the usefulness of analytics during disruption.

The expected direction must therefore be justified through the mechanisms involved and considered alongside evidence that technology can support resilience.

2.3 Evidence on information advantages and lending outcomes

Research provides substantial support for the informational value of digital credit assessment. Jagtiani and Lemieux (2019), studying LendingClub, show how alternative data and machine learning contribute to borrower assessment beyond conventional credit information. Their evidence supports the use of additional information when evaluating borrowers whose risk may be

incompletely represented by traditional measures. It does not directly establish how organizational risk management performance changes with perceived macroeconomic volatility.

Berg et al. (2020) similarly demonstrate that digital footprints contain information useful for predicting consumer default. They find that these indicators complement credit bureau information rather than simply replacing it. This strengthens the case for combining information sources, but the distinction between predictive information and organizational performance remains important. The usefulness of a borrower characteristic for classification does not, by itself, establish the effectiveness of subsequent monitoring, policy adjustment or recovery.

Evidence also shows that the consequences of machine learning extend beyond predictive improvement. Using United States mortgage data, Fuster et al. (2022) find that the benefits associated with machine learning are distributed unevenly across borrower groups. Their study concerns distributional outcomes rather than macroeconomic moderation. Its relevance here is that the consequences of analytics depend on the outcome being assessed; improvements in one dimension of lending should not be assumed to imply improvements across all dimensions.

These studies support the informational advantages of analytics while identifying different outcomes through which those advantages are expressed. Borrower classification, access to credit, pricing and organizational portfolio management are connected, but they are not interchangeable measures. The present study focuses on professionals' assessments of default control, recovery and portfolio quality.

2.4 Why economic instability may weaken the relationship

One explanation concern changes in the relationships learned from historical data. Gama et al. (2014) describe concept drift as change over time in the relationship between predictive inputs and outcomes.

Applied to lending, this suggests that a pattern previously associated with reliable repayment may become less informative when borrower circumstances change. Economic instability could therefore reduce the usefulness of historical information unless models and lending decisions adjust. This is a proposed mechanism; the present survey does not directly observe concept drift.

A second explanation concerns the distinction between identifying risk and preventing losses. Analytics may help a lender distinguish relatively safer borrowers without protecting those borrowers from widespread income pressures. If repayment capacity deteriorates across several borrower groups, better classification may offer less protection to overall portfolio performance. The model could retain predictive value while the organizational outcomes associated with its use become more constrained. This reasoning explains why weaker analytics–performance relationship need not imply that AI has become ineffective.

A third explanation concerns the organization's ability to act. Detecting a change in risk has limited practical value if lending limits, affordability assessments or collection arrangements remain unchanged. Dynamic capabilities theory helps explain this response problem. Teece et al. (1997) emphasize the processes through which organizations integrate and reconfigure resources as conditions change. For digital lenders, reviewing models and adjusting credit policy are plausible applications of that reasoning. Dynamic capabilities inform the explanation of possible adaptation, but they are not measured as a separate construct in this study.

Together, these mechanisms suggest that economic instability can constrain both the relevance of predictive information and the conversion of that information into effective lending

decisions. They provide a basis for expecting attenuation, while leaving room for differences in how lenders respond.

2.5 Competing evidence on resilience during economic shocks

The evidence does not support a general claim that AI performs poorly during instability. Gambacorta et al. (2024), using transaction-level data from a Chinese fintech firm, find that machine learning combined with nontraditional data predicts losses and defaults more effectively than traditional models during an adverse credit supply shock. Their findings suggest that richer information and flexible modelling can remain useful when credit conditions deteriorate. This evidence challenges any assumption that economic disruption necessarily eliminates the predictive advantage of AI.

Gambacorta, Sabatini, and Schiaffi (2025) provide further evidence that the consequences of AI depend on the lending setting and outcome examined. Their working paper links Italian banks' AI investment information with credit register data around the COVID-19 crisis. For a given relationship duration, AI-using banks offered more credit and lower rates in normal conditions, but the same additional protection was not evident during the crisis. The study examines bank–firm relationships and credit supply rather than digital lenders' portfolio management, so its findings cannot be transferred directly to the present setting.

These findings make the distinction between relative predictive performance and organizational outcomes especially important. An AI model can outperform a conventional model during a shock while the lender still faces weaker repayment and recovery conditions. The present hypothesis concerns whether the association between organizational analytics capability and perceived risk management performance becomes weaker as perceived volatility increases. It does not predict that AI will necessarily underperform conventional scoring.

2.6 Literature synthesis and hypothesis

The reviewed evidence establishes that machine learning and alternative data can improve borrower assessment, that their consequences differ across lending outcomes, and that analytical advantages can persist during adverse conditions. What these studies do not directly establish is whether perceived macroeconomic volatility changes the relationship between organizational AI analytics and perceived credit risk management performance among Nigerian digital lenders.

The contribution sought here is therefore specific. The study connects an organizational capability with an environmental condition and examines their interaction in a professional survey. It extends the discussion beyond whether analytics supplies useful information to whether its relationship with broader risk management performance varies under economic pressure. Because the moderator is perceptual, the analysis concerns differences in respondents' assessments of exposure and its consequences, rather than observed changes in national macroeconomic volatility over time.

Contingency theory supports this conditional argument. When economic instability changes the relevance of borrower information or constrains the organization's response, the performance advantage associated with analytics may become smaller. The competing evidence on resilience prevents this expectation from being treated as inevitable and makes the direction of the relationship an empirical question.

H1: Higher perceived macroeconomic volatility weakens the positive association between AI-driven predictive analytics and perceived credit risk management performance.

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3 Research methodology

3.1 Research design and study setting

The study used a quantitative, cross-sectional survey to examine the relationship between AI-driven predictive analytics and credit risk management performance, including the moderating role of perceived macroeconomic volatility. Data were collected from professionals working in digital lending firms and dedicated digital lending units of regulated financial institutions in Lagos State, Nigeria.

The survey captured respondents' assessments of organizational practices and performance at one point in time. This design allowed the proposed relationships to be examined across participants, but it could not establish whether changes in analytics preceded changes in performance. The findings are therefore interpreted as associations.

3.2 Sampling and respondents

Eligible participants worked in credit assessment, risk management, compliance, data analytics, finance or lending operations. Their responsibilities provided a basis for assessing the practices examined in the study. Organizations were selected purposively according to their involvement in digitally enabled lending. The sampling procedure specified functional stratification, proportionate allocation and random selection of eligible employees within the selected strata.

The final analytical sample comprised 185 complete responses, with no unusable questionnaires recorded. The sampling plan identified an accessible population of approximately 400 employees, a minimum sample of 200 and an intended distribution of 220 questionnaires. The fieldwork records available for this analysis do not reconcile these planned figures with the final response count. Consequently, a verified response rate is not reported.

The sample included 127 men and 58 women. Respondents aged 30–39 years formed the largest age group, accounting for 87 participants. Compliance officers and credit analysts contributed 42 responses each, followed by finance or operations managers with 36, data analysts with 34 and risk officers with 31. Of the respondents, 129 described their organizations as fintech firms and 56 as digital-only banks. These figures represent respondents rather than distinct organizations.

The number of participating firms and the distribution of respondents across them were not documented. This matters because employees from the same organization may provide related assessments. Without firm identifiers, within-firm agreement and dependence could not be evaluated. The analysis therefore does not treat the 185 respondents as 185 independent firms.

3.3 Measurement of the constructs

The questionnaire used five-point agreement scales ranging from strongly disagree to strongly agree. AI-driven predictive analytics, alternative data utilization, regulatory compliance, perceived macroeconomic volatility and credit risk management performance were specified as reflective constructs.

AI analytics items addressed machine learning use, automated credit assessment, data-processing capacity, model updating, workflow integration and organizational investment. Alternative data items concerned the use of information beyond conventional credit records, while compliance items addressed regulatory and governance practices.

Credit risk management performance was assessed through respondents' perceptions of default control, nonperforming loan reduction, recovery effectiveness, portfolio improvement and

comparative performance. The construct measures perceived organizational outcomes rather than audited loan losses or independently observed default rates.

The volatility measure covered inflationary pressure, exchange rate effects, model reliability, credit-policy adjustment and overall credit risk. It therefore captures perceived economic exposure and its consequences, rather than the statistical volatility of a macroeconomic series. Some items also concern organizational responses and model effectiveness, creating possible overlap with the capability and performance measures.

The measurement records contain differences that prevent the final indicator specification from being confirmed. Compliance has seven items in the descriptive summaries and six in the loading tables; volatility has five and six items respectively. The available questionnaire lists five items per construct. The estimates are retained as reported, but their interpretation remains provisional pending reconciliation of the administered instrument, coding and model specification.

3.4 Model specification and estimation

Data were analysed using SPSS and SmartPLS. Measurement assessment preceded structural model estimation, following the general reporting approach described by Hair et al. (2019). The analysis considered indicator loadings, internal consistency, convergent validity and discriminant validity before interpreting the structural relationships.

The full model was specified as:

$$\mathbf{CRMP}_i = \boldsymbol{\beta}\mathbf{0} + \boldsymbol{\beta}\mathbf{1}\mathbf{AIPA}_i + \boldsymbol{\beta}\mathbf{2}\mathbf{ADU}_i + \boldsymbol{\beta}\mathbf{3}\mathbf{RC}_i + \boldsymbol{\beta}\mathbf{4}\mathbf{MV}_i + \boldsymbol{\beta}\mathbf{5}(\mathbf{AIPA}_i \times \mathbf{MV}_i) + \boldsymbol{\varepsilon}_i$$

Here, CRMP denotes credit risk management performance;
AIPA, AI-driven predictive analytics;
ADU, alternative data utilization; RC, regulatory compliance; and
MV, perceived macroeconomic volatility

The interaction coefficient, β_5, tests the hypothesis that higher perceived volatility weakens the analytics–performance relationship.

Structural significance was assessed using 5,000 bootstrap resamples. Interpretation considered the direction and magnitude of the coefficients, their statistical significance and the reported effect sizes. Sample adequacy was not inferred from the observation count alone, since it also depends on the expected effects and estimation conditions (Kock & Hadaya, 2018).

The available output does not identify the interaction construction method, centring convention or bootstrap confidence intervals. Conditional slopes and volatility thresholds are therefore not presented. These details are needed to reproduce the moderation analysis and interpret the main effects at a clearly defined reference value.

3.5 Common method considerations and research ethics

Respondents assessed the explanatory variables, moderator and outcome through the same questionnaire. Shared response tendencies may therefore account for some of their covariance. The first-factor diagnostic was considered, but it was not treated as sufficient evidence that common method bias was absent, consistent with the concerns discussed by Podsakoff et al. (2003).

The research protocol specified institutional permission, voluntary informed consent, anonymity and confidential storage. The approving institution, approval reference and fieldwork dates were not included in the available documentation and require confirmation.

Results are presented in aggregate form to protect respondents and participating organizations.

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4 Results

4.1 Descriptive statistics and measurement assessment

Table 1 presents the descriptive and measurement estimates. Compliance recorded the highest mean, followed by AI analytics, alternative data utilization and credit risk management performance. Perceived volatility had the lowest mean. These differences describe respondents' assessments; they do not establish the contribution of any individual practice to performance.

Table 1 Descriptive statistics and measurement estimates

Construct	Mean	Reported SD	Cronbach's alpha	Composite reliability	AVE
AI analytics	3.82	0.8	0.903	0.923	0.63
Alternative data utilization	3.7	0.83	0.889	0.913	0.6
Regulatory compliance	3.87	0.81	0.914	0.93	0.66
Perceived macroeconomic volatility	3.28	0.84	0.876	0.909	0.67
Credit risk management performance	3.63	0.83	0.921	0.937	0.68

Note. SD denotes the standard deviation reported in the construct summaries; AVE denotes average variance extracted. The SD values have not been independently verified as the standard deviations of respondent-level composite scores.Indicator loadings ranged from 0.781 to 0.874 for AI analytics, 0.748 to 0.853 for alternative data, 0.789 to 0.874 for compliance, 0.792 to 0.857 for volatility and 0.826 to 0.902 for performance. Composite reliability ranged from 0.909 to 0.937, while reported AVE values ranged from 0.602 to 0.681.

HTMT ratios ranged from 0.298 to 0.782, below the conservative threshold of 0.85 discussed by Henseler et al. (2015). These estimates provide preliminary support for construct separation. They do not resolve the differences in indicator documentation, however, and several reported AVE values differ from the means of the squared standardized loadings listed for their constructs. The measurement results therefore require verification before they can support firm conclusions about validity.

No missing responses or excluded outliers were recorded. The first factor accounted for 31.84 percent of indicator variance. This result does not rule out shared method effects, particularly because some performance items explicitly attribute improved outcomes to analytics.

4.2 Structural relationships and hypothesis testing

Table 2 presents the estimates from the full structural model.

Table 2 Structural path estimates

Relationship	β	Standard error	t-value	p-value	f^2
AI analytics → Performance	0.382	0.056	6.821	<0.001	0.29
Alternative data → Performance	0.291	0.057	5.105	<0.001	0.18
Compliance → Performance	0.247	0.054	4.574	<0.001	0.14
Volatility → Performance	−0.118	0.057	2.07	0.038	0.04
AI analytics × Volatility → Performance	−0.163	0.059	2.763	0.006	0.06

Note. Estimates refer to 185 responses and 5,000 bootstrap resamples. Performance denotes perceived credit risk management performance.

The analytics–volatility interaction was negative and statistically significant ($\beta = -0.163$, $t = 2.763$, $p = 0.006$). This supports the proposed weakening relationship within the estimated model. Its reported f^2 of 0.063 indicates a small incremental contribution under the conventional effect-size

thresholds adopted in the analysis. Statistical significance should therefore be distinguished from a large practical effect.

The AI analytics coefficient was positive and significant ($\beta = 0.382$, $p < 0.001$). Because the model includes an interaction, this coefficient describes the analytics–performance relationship at the moderator's zero reference. The undocumented scaling convention prevents that reference from being identified confidently as the sample average. The direct volatility coefficient ($\beta = -0.118$, $p = 0.038$) is similarly conditional on the AI analytics reference.

The negative interaction indicates that the estimated analytics slope declines as volatility increases. It does not establish whether that slope remains statistically positive throughout the observed range or identify a point at which analytics ceases to be useful. Those conclusions require conditional estimates and their uncertainty.

Alternative data utilization and compliance were also positively associated with performance, with coefficients of 0.291 and 0.247 respectively. The model did not estimate their interactions with volatility, so these findings do not establish whether either practice buffers economic pressure.

4.3 Explanatory performance and model diagnostics

Structural VIF values ranged from 1.76 to 2.43, including 2.43 for the interaction. The full model yielded $R^2 = 0.684$ and adjusted $R^2 = 0.676$. Together, the included predictors accounted for 68.4 percent of the variance in perceived performance. This explained variance cannot be attributed to AI analytics or moderation alone.

The reported Q^2 was 0.487, SRMR was 0.051 and NFI was 0.918. These statistics describe different aspects of the estimated model, but they do not resolve uncertainty about measurement specification or dependence among respondents from the same organization.

4.4 Predictive assessment

PLS prediction errors were lower than those of the linear benchmark for all seven performance indicators, as shown in Table 3.

Table 3 Prediction errors for performance indicators

Indicator	PLS RMSE	Linear benchmark RMSE
CRMP1	0.521	0.556
CRMP2	0.548	0.577
CRMP3	0.497	0.534
CRMP4	0.563	0.587
CRMP5	0.518	0.549
CRMP6	0.536	0.571
CRMP7	0.544	0.582

Note. RMSE denotes root mean squared error.

The comparison favours the PLS model within the available output. Its interpretation remains limited by the absence of cross-validation settings, prediction folds and indicator-specific Q^2predict values. Shmueli et al. (2019) distinguish predictive assessment from explanatory fit; the reported R^2 alone cannot establish performance on new observations. The prediction results also concern survey indicators, not actual loan defaults or losses.

Supplementary importance–performance analysis produced indices of 81.64 for AI analytics, 79.52 for alternative data, 77.86 for compliance and 69.74 for volatility. Corresponding importance values were 0.382, 0.291, 0.247 and −0.118. These figures are retained as

supplementary estimates. The rescaling procedure was not documented, and a single importance value does not fully represent the conditional relationships in an interaction model. They therefore provide insufficient grounds for ranking investment returns or prescribing budgets.

4.5 Interpretation of the findings

The principal finding is weaker positive analytics–performance relationship at higher levels of perceived macroeconomic volatility. This pattern is consistent with the proposed environmental contingency, but it does not demonstrate that an observed economic shock reduced algorithmic accuracy or caused greater loan losses.

The evidence is best understood as a conditional association among professional assessments. Its substantive value depends on confirming the measurement specification, documenting the sampling structure and completing the moderation output. These checks are necessary to determine how confidently the reported pattern can be interpreted and reproduced.

5 Discussion and implications

5.1 Macroeconomic conditions and the value of analytics

The main finding is that the positive association between AI-driven predictive analytics and perceived credit risk management performance becomes weaker as perceived macroeconomic volatility increases. The interaction coefficient was negative and statistically significant ($\beta = -0.163$, $p = 0.006$), although its incremental effect size was small ($f^2 = 0.063$). Economic conditions therefore appear relevant to the relationship, but the result should not be interpreted as evidence that instability removes the benefits of analytics.

Contingency theory offers a useful explanation. Donaldson (2001) argues that organizational effectiveness depends on the fit between internal arrangements and operating conditions. In digital lending, analytics may support borrower assessment while changing income and business conditions limit the outcomes associated with those assessments. The finding is consistent with this argument: the relationship between a technological capability and performance varies with the environment in which that capability is used.

One possible explanation is that historical borrower information becomes less informative as economic circumstances change. Gama et al. (2014) explain how changes in the relationship between predictive inputs and outcomes can reduce the usefulness of previously learned patterns. Applied to lending, a transaction history that once indicated reliable repayment may become less useful when the borrower's disposable income falls or business costs rise. The present study does not observe model errors over time, so it cannot establish that concept drift caused the interaction. It identifies a pattern for which changing information relevance is a plausible explanation.

A second possibility concerns the lender's response. Detecting an increase in risk does not ensure that loan limits, affordability assessments or collection practices will change promptly. The result may therefore reflect constraints on converting analytical information into effective decisions, as well as changes in borrower circumstances. These explanations remain propositions for further investigation rather than mechanisms demonstrated by the survey.

5.2 Relationship with previous research

The findings complement research on the informational advantages of machine learning and alternative data. Jagtiani and Lemieux (2019) show how these approaches extend borrower assessment beyond conventional credit information, while Berg et al. (2020) demonstrate that digital footprints can complement credit bureau scores. These studies help explain why analytics may be positively associated with risk management performance. The present analysis adds an

environmental qualification by examining whether that association varies with perceived economic instability.

The negative interaction also needs to be considered alongside evidence that AI can remain useful during adverse conditions. Gambacorta et al. (2024) find that machine learning combined with nontraditional data outperforms traditional models in predicting losses and defaults during a credit supply shock in China. Their result concerns comparative prediction, whereas the present study concerns professionals' assessments of organizational risk management. A model may retain an advantage over conventional scoring while the lender experiences worsening repayment conditions across its portfolio. The two findings therefore address different aspects of lending performance.

Research on Italian banks provides another reason to avoid assuming that the benefits of AI remain unchanged across conditions. Gambacorta, Sabatini, and Schiaffi (2025) report that, for a given relationship duration, AI-using banks supplied more credit at lower rates in normal conditions, but the same additional protection was not evident during the COVID-19 crisis. Their setting and outcomes differ from those examined here, yet the study reinforces the importance of specifying which benefit is being assessed and under what conditions.

Taken together, the evidence supports a conditional view of analytics. Better information can improve lending decisions, but its organizational value depends on borrower exposure, the outcome being measured and the lender's capacity to respond.

5.3 Theoretical implications

The study's main theoretical contribution is to identify an environmental condition associated with variation in the analytics–performance relationship. The result is consistent with contingency theory because it places the use of analytics within its operating environment, rather than treating technology adoption as sufficient for better performance. This interpretation remains bounded by the perceptual measures and cross-sectional design.

The organizational capability literature helps explain why this distinction matters. Gupta and George (2016) show that analytics capability depends on a combination of resources, rather than technology investment alone. The present findings suggest that the performance associated with such capability may also vary with perceived economic pressure. They do not establish which combination of resources best preserves performance during instability.

Dynamic capabilities theory provides a basis for considering how lenders might respond. Teece et al. (1997) emphasize the organizational processes through which resources are integrated and reconfigured as conditions change. Model review, revised credit policies and adjustments to monitoring arrangements are plausible applications in lending. However, the study did not measure adaptive capability separately. It therefore cannot conclude that these practices offset the weakening relationship.

The wider implication for international business research concerns the transfer of analytical practices across markets. A lending system that proves useful in one environment may require different data, oversight or decision processes elsewhere. This is a proposition arising from the environmental fit argument, rather than an observed cross-country effect. Comparative research is needed to establish how institutional and economic differences influence the relationship.

5.4 Implications for digital lending management

Managers should assess analytics through both model performance and lending outcomes. A model may rank borrowers effectively while portfolio losses rise because repayment conditions have deteriorated. Monitoring should therefore connect predictions with actual defaults, recovery rates and loss severity across loan vintages and borrower groups. This would help lenders distinguish weaknesses in scoring from changes in borrower circumstances or collection performance.

Model updating should follow evidence of deterioration and a clear validation process. Frequent retraining is not necessarily useful when recent observations are limited or unrepresentative. Comparing an existing model with a challenger and evaluating both on a later time period can provide a stronger basis for deciding whether a change improves performance. The concept drift literature supports the need to evaluate adaptation as predictive relationships change, rather than assuming that a model remains reliable indefinitely (Gama et al., 2014).

Macroeconomic information should also be interpreted in relation to borrower exposure. Inflation may affect salaried households differently from informal traders, while exchange rate movements may matter more directly to businesses dependent on imported goods. Scenario analysis can examine these differences alongside cash flow and affordability. The aggregate survey does not estimate such segment-specific effects, so it cannot justify a common threshold for reducing credit across all borrowers.

The positive associations for alternative data utilization and compliance suggest that analytics operates within a wider information and governance system. These coefficients do not establish that either practice protects lenders from economic instability, since their interactions with volatility were not tested. Decisions about expanding data sources or changing governance arrangements should therefore be evaluated separately, with attention to relevance, data quality and borrower protection.

5.5 Implications for boards and supervisory oversight

For boards, the findings draw attention to the connection between analytical signals and management action. Oversight should examine how changes in model performance led to decisions about approval criteria, credit limits, portfolio concentrations and collection practices. Evidence that a model detects risk is incomplete without evidence of how the organization responds.

Supervisory assessment can similarly consider whether lenders validate their systems under changing conditions and document the consequences of model and policy adjustments. The compliance construct combines several organizational practices, however, and its positive coefficient cannot identify the effect of a particular supervisory requirement. The study supports closer examination of governance processes without establishing which individual measure produces better outcomes.

6 Limitations and further research

The findings require several qualifications. The cross-sectional design does not establish the timing of the relationships. Better-performing lenders may have greater resources to invest in analytics, while respondents with favourable views of their organizations may assess several practices positively. The associations should therefore not be read as causal effects.

The moderator captures perceptions of economic exposure and partly includes its consequences. Respondents experiencing weaker portfolio outcomes may view the environment more negatively, while items concerning model deterioration may overlap with performance. Shared measurement also leaves room for common method effects (Podsakoff et al., 2003). Future

studies should distinguish external exposure, perceived instability and organizational response more clearly.

The sampling and measurement records also constrain interpretation. The number of distinct participating firms was not documented, preventing an assessment of dependence among respondents from the same organization. Differences between the questionnaire, indicator summaries and loading tables must be reconciled before stronger measurement claims can be made. These issues require verification of the research records rather than further interpretation of the existing coefficients.

Longitudinal research could connect changes in analytics, borrower exposure and realized loan outcomes. Complete moderation output, including confidence intervals and conditional slopes, would clarify the relationship across the observed range of volatility. Comparisons across countries and lending models could then establish whether the pattern varies with institutional conditions, borrower characteristics or the organization's capacity to adapt.

7 Conclusion

AI-driven predictive analytics was positively associated with perceived credit risk management performance, but that relationship weakened as perceived macroeconomic volatility increased. The interaction was statistically significant and small in incremental effect size. The finding supports attention to the conditions under which analytics is used, alongside investment in the technology itself.

For digital lenders, the practical implication is to connect model validation with borrower affordability and lending policy. The study does not show that AI loses its predictive advantage during instability or that a particular adaptation strategy prevents losses. It identifies a conditional relationship that merits further examination using verified measurement records and repeated observations of lending outcomes.

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