

Digital Lending, Accounting Disclosure Quality, and Banking Risk: Implications for Financial Stability

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Abstract

Digital lending has become an important component of modern financial intermediation as banks, fintech firms, platform companies and non-bank financial institutions increasingly use alternative data, digital transactions and algorithmic credit scoring to originate, price and monitor credit. Although digital lending can improve credit access, reduce information asymmetry and support financial inclusion, it also creates new challenges for accounting disclosure, banking risk management and macroeconomic stability. This study examines the cross-disciplinary integration of digital lending data into accounting disclosure and banking risk frameworks, with emphasis on implications for financial intermediation and financial-system resilience. Using a proposed country-year panel framework covering 44 countries from 2015 to 2023, the study investigates the relationship between digital lending intensity, accounting disclosure quality, banking risk, financial intermediation and macroeconomic stability. Digital lending intensity is measured as digital lending volume scaled by gross domestic product, while banking risk is proxied by non-performing loans. Bank Z-score and capital adequacy are used as alternative measures of financial stability. Accounting disclosure quality is proxied by IFRS adoption or, alternatively, by a disclosure index based on expected credit loss disclosure, digital lending exposure, credit risk segmentation, model risk disclosure and macroeconomic assumption reporting. The illustrative findings suggest that digital lending intensity is positively associated with banking risk, while accounting disclosure quality reduces this risk and moderates the relationship between digital lending and banking risk. The results further suggest that digital lending can deepen financial intermediation by expanding private credit, but its stability effects depend on the strength of disclosure, governance and regulatory oversight. The study contributes to fintech, accounting and banking literature by showing that digital lending data should not remain limited to operational credit-scoring systems; rather, they should be integrated into IFRS 7 risk disclosure, IFRS 9 expected credit loss estimation, bank risk dashboards, model validation processes, supervisory reporting and macroprudential monitoring. The study concludes that sustainable digital lending requires transparent accounting disclosure, robust model governance and effective integration of digital credit data into banking risk frameworks.

Keywords: digital lending; accounting disclosure; banking risk; IFRS 9; IFRS 7; fintech credit; financial intermediation; macroeconomic stability; expected credit loss; digital finance.

1. Introduction

Digital lending has become an important feature of modern financial intermediation as banks, fintech firms and platform-based lenders increasingly use digital transactions, alternative data and algorithmic credit scoring to originate and monitor credit. Unlike traditional lending, which relies mainly on collateral, credit history and financial statements, digital lending uses high-frequency borrower data such as mobile-money records, e-commerce transactions, repayment behavior and platform activity to assess creditworthiness (Berg et al., 2020; Jagtiani & Lemieux, 2019; World Bank, 2025). Although digital lending can improve credit access and reduce information asymmetry, it also creates new risks for financial reporting, banking supervision and macroeconomic stability. Automated lending systems may increase credit expansion, borrower over-indebtedness, model risk and algorithmic opacity, especially where disclosure and regulatory oversight are weak (Fuster et al., 2022; Gambacorta et al., 2020; Basel Committee on Banking Supervision [BCBS], 2024). These risks make digital lending relevant not only to fintech innovation but also to accounting disclosure and banking risk governance. From an accounting perspective, digital lending data are important for financial instrument disclosure and expected credit loss estimation. IFRS 7 requires entities to disclose the nature and extent of risks arising from financial instruments, while IFRS 9 requires forward-looking expected credit loss recognition based on reasonable and supportable information (International Accounting Standards Board [IASB], 2014, 2021). Digital lending data can therefore provide early signals of credit deterioration, but such data must be reliable, auditable and properly disclosed.

This study examines the integration of digital lending data into accounting disclosure and banking risk frameworks, focusing on implications for financial intermediation and macroeconomic stability. Using a proposed country-year panel framework for 2015–2023, the study investigates whether digital lending intensity affects banking risk and whether accounting disclosure quality moderates this relationship. The study contributes to fintech, accounting and banking literature by showing that digital lending data should be incorporated into IFRS-based disclosure, expected credit loss models, risk governance systems and macroprudential monitoring.

2. Literature Review

2.1 Digital Lending and the Transformation of Financial Intermediation

Financial intermediation theory views banks as institutions that reduce information asymmetry, monitor borrowers, transform maturities, and allocate credit within the economy (Diamond, 1984; Diamond & Dybvig, 1983). Traditional lending relies on financial statements, collateral, credit histories, relationship banking, and delegated monitoring (Berger & Udell, 1995, 2006). However, digital lending has transformed this model through technology-enabled credit assessment, automated loan processing, and alternative data-driven risk evaluation (Philippon, 2016; Claessens et al., 2018). Digital lending includes fintech credit, peer-to-peer lending, marketplace lending, mobile-money credit, platform-based lending, and digital bank lending (Tang, 2019; Frost et al., 2019). Unlike conventional lending, it uses high-frequency borrower data such as transaction histories, wallet activity, e-commerce sales, platform behavior, utility payments, and other alternative data sources (Berg et al., 2020; Jagtiani & Lemieux, 2019; World Bank, 2025). The literature suggests that digital lending may improve financial intermediation by reducing information asymmetry, lowering transaction costs, and expanding credit access for borrowers with limited credit histories (Beck et al., 2007; Demirgüç-Kunt et al., 2018). However, it may also create risks through rapid credit expansion, opaque algorithms, weak model explainability, and limited regulatory visibility (Buchak et al., 2018; Tang, 2019; Gambacorta et al., 2020). Thus,

digital lending may reduce borrower-lender information asymmetry while increasing information gaps between lenders, investors, auditors, and supervisors.

2.2 Alternative Data, Algorithmic Credit Scoring, and Model Risk

Alternative data are central to digital lending and include mobile-money activity, payment histories, online purchases, platform sales, geolocation patterns, utility payments, and other non-traditional borrower indicators (Berg et al., 2020; World Bank, 2025). These data can improve credit access for borrowers without conventional credit records or audited financial statements (Jagtiani & Lemieux, 2019; Demirgüç-Kunt et al., 2018). Prior studies show that digital footprints and machine-learning models can improve default prediction and credit allocation (Berg et al., 2020; Jagtiani & Lemieux, 2019). However, alternative data also introduce model risk, ethical concerns, and transparency problems. Machine-learning credit models may lack explainability and may produce biased outcomes if the underlying data reflect social, economic, or geographic inequalities (Fuster et al., 2022; Gambacorta et al., 2020; Akerlof, 1970; Stiglitz & Weiss, 1981). Digital credit models may also become unreliable during macroeconomic stress, when borrower behavior and economic conditions change rapidly (Schularick & Taylor, 2012; IMF, 2023). Therefore, digital lending data require strong governance, validation, documentation, and disclosure because model outputs can affect loan classification, expected credit loss estimation, provisioning, and risk disclosure (IASB, 2014, 2021; BCBS, 2013).

2.3 Accounting Disclosure, IFRS 7, and Digital Lending Risk

Accounting disclosure reduces information asymmetry between firms and external stakeholders (Healy & Palepu, 2001; Leuz & Wysocki, 2016). In banking, disclosure is particularly important because banks are highly leveraged and exposed to credit, liquidity, market, operational, and systemic risks (Laeven & Levine, 2009; Barth, 2013). IFRS 7 requires entities to disclose the significance of financial instruments and the nature and extent of risks arising from them (IASB, 2021). For banks and digital lenders, this includes credit risk, liquidity risk, market risk, concentration risk, and risk management practices. In digital lending, IFRS 7 implies disclosure of digital credit exposure, portfolio quality, borrower segmentation, platform concentration, and risk-management processes. However, many banks still focus on traditional credit risk categories such as sector, geography, collateral, and maturity, while giving limited attention to digital lending channels, alternative credit scoring, fintech partnerships, algorithmic model risk, and platform concentration. This creates a disclosure gap between how digital credit is originated and how credit risk is reported. Integrating digital lending data into financial instrument disclosure can improve transparency, market discipline, and investor assessment of digital credit risk (Barth et al., 2008; Leuz & Wysocki, 2016).

2.4 IFRS 9 Expected Credit Loss and Digital Lending Data

IFRS 9 introduced a forward-looking expected credit loss model for financial instruments (IASB, 2014). Under IFRS 9, entities must recognize expected credit losses using reasonable and supportable information about past events, current conditions, and future economic forecasts (IASB, 2016). This approach enables earlier recognition of credit deterioration. Digital lending data are relevant to IFRS 9 because they can provide timely borrower-risk signals. Repayment delays, declining digital wallet balances, reduced e-commerce sales, repeated loan rollovers, and deteriorating transaction patterns may indicate a significant increase in credit risk before formal default occurs. These indicators can support loan staging, probability of default estimation, loss-given-default assessment, and management overlays. However, digital lending data may be incomplete, unstable, non-standardized, or difficult to verify. Machine-learning credit scores may also be difficult for auditors to interpret, while third-party data sources may change over time. These issues affect the reliability and auditability of expected credit loss estimates. Therefore, the

Basel Committee's principles on accurate, complete, timely, and adaptable risk data are relevant to digital lending and IFRS 9 implementation (BCBS, 2013).

2.5 Banking Risk Frameworks and Digital Lending

Banking risk frameworks are designed to identify, measure, monitor, and control risks such as credit risk, liquidity risk, market risk, operational risk, model risk, and systemic risk (BCBS, 2013, 2024). Digital lending affects all these risk categories. The most direct effect is on credit risk. Digital lending may improve borrower screening through richer data, but it may also increase risk if models overestimate repayment capacity or if lenders expand credit too aggressively (Tang, 2019; Buchak et al., 2018). Digital borrowers may also obtain loans from multiple platforms, creating hidden leverage and debt-stacking risk. Digital lending also increases operational and technology risk because loan origination depends on data pipelines, APIs, cloud systems, automated decision tools, cybersecurity controls, and third-party providers (BCBS, 2024). In addition, model risk remains a major concern because algorithms trained on historical data may perform poorly during macroeconomic shocks, leading to mispriced loans, delayed loss recognition, or excessive credit tightening (Fuster et al., 2022; Gambacorta et al., 2020). This is especially important for IFRS 9 because expected credit loss models depend on forward-looking assumptions.

2.6 Digital Lending, Financial Stability, and Macroeconomic Risk

The relationship between digital lending and macroeconomic stability is mixed. Digital lending may support economic growth by improving credit access, deepening financial intermediation, and increasing the efficiency of capital allocation (Philippon, 2016; Frost et al., 2019). It may also promote financial inclusion and support household consumption and SME investment (Beck et al., 2007; Demirgüç-Kunt et al., 2018). However, rapid credit growth can contribute to financial instability (Schularick & Taylor, 2012). Digital lending may amplify this risk because platforms can scale credit quickly, automate approvals, and expand lending during boom periods. If underwriting standards weaken or borrower leverage increases, digital lending may worsen default risk during downturns. The IMF (2023) notes that fintech's effect on financial stability depends on the type of fintech activity. Digital lending is particularly important because it directly affects credit creation, borrower leverage, and repayment risk. It may also create systemic risk through common data sources, similar algorithms, and third-party platform dependence. During stress periods, lenders using similar models may reduce credit supply simultaneously, intensifying macroeconomic downturns. Therefore, digital lending requires both microprudential and macroprudential monitoring.

2.7 Accounting Disclosure Quality as a Moderating Mechanism

Accounting disclosure quality may moderate the relationship between digital lending and banking risk. High-quality disclosure improves transparency, reduces information asymmetry, and strengthens market discipline (Healy & Palepu, 2001; Barth et al., 2008; Leuz & Wysocki, 2016). In digital lending, disclosure quality can improve the visibility of credit risk models, digital loan exposures, expected credit loss assumptions, concentration risk, and macroeconomic overlays. IFRS adoption is often associated with improved financial reporting comparability and accounting quality (Barth et al., 2008; Barth, 2013). In countries with stronger disclosure environments, banks may be more likely to explain credit risk assumptions, disclose expected credit loss methodologies, and provide transparent information about financial instrument risks. This may reduce the risk that digital lending expands without adequate monitoring. Conversely, in weak disclosure environments, digital lending may increase banking risk because investors and regulators may not fully observe credit deterioration, model weaknesses, or borrower concentration. This creates the possibility that accounting disclosure quality weakens the positive

relationship between digital lending intensity and banking risk. Therefore, disclosure quality is not only a reporting outcome; it may also function as a governance mechanism that influences financial stability.

2.8 Literature Gap

Although prior studies have examined fintech lending, alternative credit scoring, banking risk, and accounting disclosure separately, limited research integrates these areas into a single framework. Studies on fintech lending emphasize credit access, competition, and alternative data (Berg et al., 2020; Jagtiani & Lemieux, 2019; Tang, 2019). Accounting studies focus on disclosure quality, IFRS adoption, and expected credit loss reporting (Barth et al., 2008; Leuz & Wysocki, 2016; IASB, 2014). Banking studies examine risk governance, capital adequacy, and financial stability (Laeven & Levine, 2009; BCBS, 2013; BCBS, 2024). However, few studies explain how digital lending data should be integrated into accounting disclosure and banking risk frameworks. This study addresses the gap by examining digital lending as a cross-disciplinary issue involving fintech innovation, accounting disclosure, banking risk, financial intermediation, and macroeconomic stability. It argues that digital lending data should not remain confined to operational credit scoring systems. Instead, such data should inform IFRS 7 risk disclosure, IFRS 9 expected credit loss estimation, bank risk management, supervisory reporting, and macroprudential monitoring.

3. Theoretical Framework and Hypotheses Development

3.1 Theoretical Foundation

This study is anchored on information asymmetry theory, agency theory, and financial stability theory. These theories explain how digital lending changes the information structure of credit markets, how weak disclosure may increase managerial risk-taking, and how digital credit expansion may affect banking and macroeconomic stability. Since the study connects fintech, accounting disclosure, banking risk, and financial intermediation, a multi-theoretical approach is appropriate.

3.2 Information Asymmetry Theory

Information asymmetry occurs when one party has more or better information than another party in a transaction (Akerlof, 1970). In credit markets, borrowers usually know more about their repayment capacity than lenders, which may cause adverse selection and credit rationing (Stiglitz & Weiss, 1981). Traditional banks reduce this problem through screening, monitoring, collateral, and relationship lending (Diamond, 1984; Berger & Udell, 1995). Digital lending can reduce borrower-lender information asymmetry by using alternative data, digital transaction records, mobile-money activity, platform sales, and algorithmic credit scoring (Berg et al., 2020; Jagtiani & Lemieux, 2019). However, it may create a new form of information asymmetry between lenders and external stakeholders, because investors, auditors, and regulators may not fully understand how digital lending data and models are used. Therefore, high-quality accounting disclosure is needed to make digital credit risks more transparent.

3.3 Agency Theory

Agency theory explains conflicts between managers and stakeholders when managers control information and may act in their own interest (Jensen & Meckling, 1976). In digital lending, managers may be incentivized to expand loan portfolios rapidly to increase revenue, market share, or platform valuation. If disclosure is weak, stakeholders may not observe the riskiness of digital credit growth until losses emerge. Accounting disclosure can reduce agency problems by improving transparency and monitoring (Healy & Palepu, 2001; Leuz & Wysocki, 2016). In digital lending, disclosure of expected credit loss assumptions, model risk, fintech partnerships, and digital lending exposure can discipline managerial behavior and reduce excessive risk-taking.

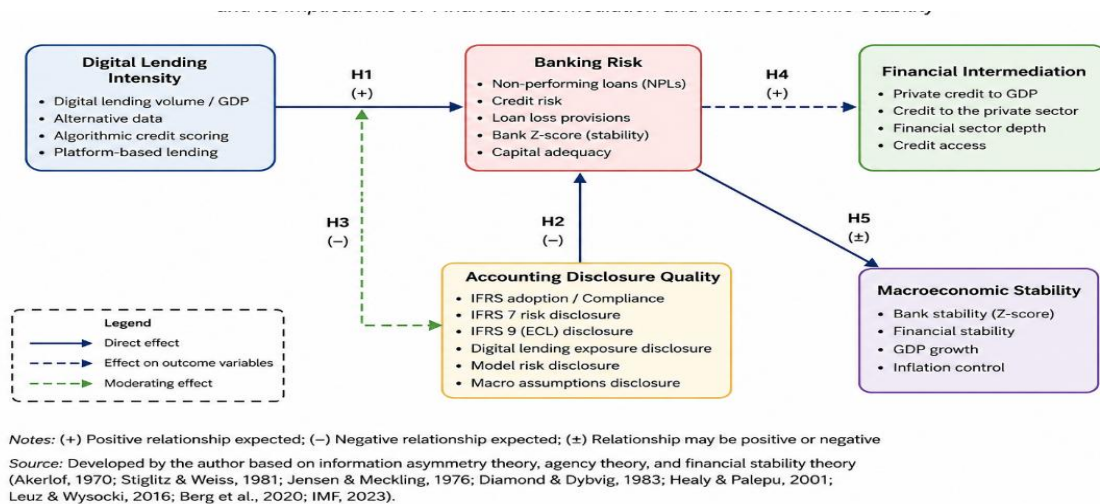
3.4 Financial Stability Theory

Financial stability theory focuses on the ability of the financial system to allocate resources, absorb shocks, and support economic activity without systemic disruption. Banks are central to stability because they create credit, transform liquidity, and transmit financial shocks (Diamond & Dybvig, 1983; Schularick & Taylor, 2012). Digital lending may support stability by improving credit access and financial intermediation, but it may also increase instability if it encourages excessive credit growth, borrower over-indebtedness, algorithmic herding, and procyclical lending (Fuster et al., 2022; IMF, 2023). Thus, digital lending requires strong disclosure, model governance, and risk monitoring.

3.5 Conceptual Framework

The study proposes that digital lending intensity affects banking risk, while accounting disclosure quality moderates this relationship. Digital lending may influence banking risk through credit expansion, alternative credit scoring, borrower debt accumulation, and model risk. Accounting disclosure quality may weaken this risk effect by improving transparency, expected credit loss recognition, and stakeholder monitoring.

Figure 1. Conceptual Framework of Digital Lending, Accounting Disclosure Quality and Banking Risk



4. Methodology

4.1 Research Design

This study adopts a quantitative empirical research design using country-year panel data. The study examines the relationship between digital lending intensity, accounting disclosure quality, banking risk, financial intermediation, and macroeconomic stability. A panel research design is appropriate because the study observes several countries over multiple years, allowing the analysis to capture both cross-country differences and changes over time. The study covers the period 2015–2023. This period is suitable because digital lending expanded significantly during these years due to the growth of fintech platforms, mobile banking, embedded finance, digital payments, and alternative credit scoring. The period also includes important macroeconomic events, especially the COVID-19 shock, which affected credit risk, loan repayment capacity, and banking stability. The unit of analysis is the country-year. Each observation represents one country in one year. The proposed sample consists of 44 countries across Africa, Asia, Europe, Latin America, the Middle East, Oceania, and North America. The final sample may be treated as an unbalanced panel because digital lending data and banking risk indicators may not be available for all countries in all years.

4.2 Population and Sample

The population of the study consists of countries with available data on digital lending, banking risk, accounting disclosure quality, financial intermediation, and macroeconomic indicators. The sample includes countries for which relevant data can be obtained from international databases such as the Cambridge Centre for Alternative Finance, World Bank, International Monetary Fund, and IFRS-related sources. The proposed sample includes 44 countries observed over nine years, producing a maximum of 396 country-year observations.

Table 1

Proposed Country Sample

Region	Suggested countries	Number of countries
Africa	Kenya, Nigeria, South Africa, Ghana, Egypt, Tanzania, Uganda, Rwanda, Morocco, Tunisia	10
Asia	China, India, Indonesia, Malaysia, Philippines, Thailand, Vietnam, Singapore, Pakistan, Bangladesh	10
Europe	United Kingdom, Germany, France, Spain, Italy, Netherlands, Sweden, Poland, Switzerland, Ireland	10
Latin America	Brazil, Mexico, Chile, Colombia, Argentina, Peru	6
Middle East	United Arab Emirates, Saudi Arabia, Turkey, Jordan	4
Oceania	Australia, New Zealand	2
North America	United States, Canada	2
Total	Suggested global sample	44

4.3 Data Sources

The study uses secondary data from internationally recognized databases. Digital lending data are obtained from the Cambridge Centre for Alternative Finance. Banking risk and financial stability indicators are obtained from the World Bank Global Financial Development Database and the IMF Financial Soundness Indicators. Macroeconomic control variables are obtained from the World Bank World Development Indicators. Institutional quality variables are obtained from the World Bank Worldwide Governance Indicators. Accounting disclosure quality is measured using IFRS adoption or a manually constructed disclosure index from bank annual reports.

Table 2

Data Sources and Variable Coverage

Data source	Variables obtained	Frequency	Level	Study use
Cambridge Centre for Alternative Finance	Digital lending volume; fintech credit; alternative finance volume	Annual	Country-year	Main digital lending variable
World Bank Global Financial Development Database	Bank Z-score; private credit; bank stability indicators	Annual	Country-year	Banking risk and financial intermediation
World Bank World Development Indicators	GDP growth; inflation; unemployment; GDP; population	Annual	Country-year	Macroeconomic controls

IMF Financial Soundness Indicators	NPL ratio; capital adequacy; ROA; ROE	Annual quarterly	/	Country-year	Banking soundness and robustness variables
World Bank Worldwide Governance Indicators	Regulatory rule of government effectiveness	Annual		Country-year	Institutional controls
IFRS Foundation / manual coding	IFRS adoption or permitted IFRS use	Annual	/	Country-year	Accounting disclosure proxy
Bank annual reports	IFRS 9 disclosure; credit risk disclosure; digital lending disclosure; model risk disclosure	Annual		Bank-year / country-year	Alternative disclosure index

4.4 Variable Measurement

The dependent variable is banking risk. The main proxy for banking risk is the non-performing loan ratio, measured as bank non-performing loans to total gross loans. Higher NPL values indicate greater banking risk. For robustness, the study uses bank Z-score and capital adequacy ratio as alternative dependent variables. The main independent variable is digital lending intensity, measured as digital lending volume scaled by GDP. Scaling digital lending by GDP allows cross-country comparability because larger economies naturally have higher lending volumes. The moderating variable is accounting disclosure quality. The study uses IFRS adoption as the main proxy. IFRS adoption is coded as 1 if a country has adopted or permitted IFRS for listed firms or financial institutions, and 0 otherwise. As an alternative measure, the study proposes a disclosure index based on bank annual report disclosures.

Control variables include GDP growth, inflation, unemployment, private credit to GDP, regulatory quality, and rule of law.

Table 3

Variable Definition, Measurement and Data Sources

Variable code	Variable name	Role in model	Measurement	Expected sign	Data source
NPL	Non-performing loans	Main dependent variable	Bank non-performing loans to total gross loans (%)	—	World Bank / IMF FSI
ZSCORE	Bank stability	Alternative dependent variable	Bank Z-score; higher value indicates greater stability	—	World Bank GFDD
CAR	Capital adequacy	Alternative dependent variable	Regulatory capital to risk-weighted assets (%)	—	IMF FSI
DL	Digital lending volume	Independent variable	Total digital lending / fintech credit volume by country-year	+ / -	Cambridge Centre for Alternative Finance

DLGDP	Digital lending intensity	Independent variable	Digital lending volume as percentage of GDP	+ / -	CCAF and World Bank WDI
IFRS	Accounting disclosure quality	Moderator	1 if IFRS adopted or permitted; 0 otherwise	-	IFRS Foundation / manual coding
DL_IFRS	Interaction term	Moderating variable	Digital lending intensity × IFRS adoption	-	Computed
GDPG	GDP growth	Control variable	Annual GDP growth rate (%)	-	World Bank WDI
INF	Inflation	Control variable	Consumer price inflation, annual (%)	+	World Bank WDI
UNEMP	Unemployment	Control variable	Unemployment rate, total (%)	+	World Bank WDI
PCGDP	Private credit to GDP	Dependent / control variable	Domestic credit to private sector as % of GDP	+ / -	World Bank WDI / GFDD
REGQ	Regulatory quality	Control variable	Regulatory quality estimate	-	World Bank WGI
ROL	Rule of law	Control variable	Rule of law estimate	-	World Bank WGI

4.5 Construction of Accounting Disclosure Index

Although IFRS adoption provides a useful country-level proxy for accounting disclosure quality, it may not fully capture the actual quality of bank-level disclosure. Therefore, the study proposes an alternative disclosure index based on annual reports. The disclosure index is constructed using eight disclosure items. Each item is scored 1 if disclosed and 0 if not disclosed. The total disclosure score ranges from 0 to 8. The final disclosure index is calculated by dividing the total score by 8.

Table 4

Disclosure Index Construction

Disclosure item	Description	Score
IFRS 9 expected credit loss disclosure	Bank explains ECL estimation, staging or impairment methodology	0 / 1
Macroeconomic assumptions disclosure	Bank discloses forward-looking macroeconomic assumptions used in ECL	0 / 1
Credit risk segmentation	Bank reports credit exposure by sector, geography, product or risk grade	0 / 1
Digital lending exposure	Bank discloses digital lending, fintech lending or online loan exposure	0 / 1
Alternative data disclosure	Bank mentions alternative credit data, digital footprints or non-traditional credit scoring	0 / 1
Model risk disclosure	Bank discusses credit scoring, model validation, model uncertainty or algorithmic risk	0 / 1
Technology or cyber risk disclosure	Bank discloses technology, cyber, platform or digital infrastructure risk	0 / 1

Fintech partnership disclosure	Bank discloses fintech partnerships, platform lending arrangements or outsourced digital lending channels	0 / 1
Total disclosure score	Sum of all disclosure items	0–8
Disclosure index	Total disclosure score divided by 8	0–1

4.6 Model Specification

The study estimates three main models: the banking risk model, the moderation model, and the financial intermediation model.

4.6.1 Baseline Banking Risk Model

The baseline model examines the effect of digital lending intensity on banking risk.

$$NPL_{it} = \beta_0 + \beta_1 DLGDP_{it} + \beta_2 GDPG_{it} + \beta_3 INF_{it} + \beta_4 UNEMP_{it} + \beta_5 PCGDP_{it} + \beta_6 REGQ_{it} + \mu_i + \lambda_t + \epsilon_{it}$$

Where:

- NPL_{it} = non-performing loans in country i at year t
- $DLGDP_{it}$ = digital lending as percentage of GDP
- $GDPG_{it}$ = GDP growth
- INF_{it} = inflation
- $UNEMP_{it}$ = unemployment
- $PCGDP_{it}$ = private credit to GDP
- $REGQ_{it}$ = regulatory quality
- μ_i = country fixed effects
- λ_t = year fixed effects
- ϵ_{it} = error term

4.6.2 Moderation Model

The moderation model tests whether accounting disclosure quality moderates the relationship between digital lending and banking risk.

$$NPL_{it} = \beta_0 + \beta_1 DLGDP_{it} + \beta_2 IFRS_{it} + \beta_3 (DLGDP_{it} \times IFRS_{it}) + \beta_4 GDPG_{it} + \beta_5 INF_{it} + \beta_6 UNEMP_{it} + \beta_7 PCGDP_{it} + \beta_8 REGQ_{it} + \mu_i + \lambda_t + \epsilon_{it}$$

The interaction term $DLGDP_{it} \times IFRS_{it}$ captures the moderating effect of accounting disclosure quality. A negative and significant coefficient on the interaction term would indicate that stronger accounting disclosure quality reduces the risk-enhancing effect of digital lending.

4.6.3 Financial Intermediation Model

The financial intermediation model examines whether digital lending contributes to financial deepening.

$$PCGDP_{it} = \beta_0 + \beta_1 DLGDP_{it} + \beta_2 IFRS_{it} + \beta_3 (DLGDP_{it} \times IFRS_{it}) + \beta_4 GDPG_{it} + \beta_5 INF_{it} + \beta_6 UNEMP_{it} + \beta_7 REGQ_{it} + \mu_i + \lambda_t + \epsilon_{it}$$

In this model, private credit to GDP is used as the dependent variable. A positive coefficient on digital lending intensity would suggest that digital lending supports financial intermediation.

4.6.4 Macroeconomic Stability Model

The macroeconomic stability model examines whether digital lending affects broader financial stability.

$$ZSCORE_{it} = \beta_0 + \beta_1 DLGDP_{it} + \beta_2 IFRS_{it} + \beta_3 (DLGDP_{it} \times IFRS_{it}) + \beta_4 GDPG_{it} + \beta_5 INF_{it} + \beta_6 UNEMP_{it} + \beta_7 PCGDP_{it} + \beta_8 REGQ_{it} + \mu_i + \lambda_t + \epsilon_{it}$$

Bank Z-score is used as a proxy for banking stability. A higher Z-score indicates greater bank stability. Therefore, a negative coefficient on digital lending intensity would suggest that digital lending may reduce financial stability, while a positive interaction term would suggest that disclosure quality mitigates this effect.

4.7 Estimation Technique

The study estimates the models using panel regression techniques. The analysis begins with pooled ordinary least squares, followed by country fixed effects and two-way fixed effects models. The fixed effects model is preferred because it controls for unobserved country-specific characteristics that may affect banking risk, such as legal origin, financial structure, institutional history, cultural factors, and regulatory traditions. Year fixed effects are also included to control for global shocks, such as the COVID-19 pandemic, global interest rate changes, and international financial market conditions.

The general two-way fixed effects specification is:

$$Y_{it} = \beta_0 + \beta_1 X_{it} + \beta_2 Controls_{it} + \mu_i + \lambda_t + \epsilon_{it}$$

Where Y_{it} represents the dependent variable and X_{it} represents the key explanatory variable. Robust standard errors should be used to correct for heteroskedasticity. Where possible, standard errors may be clustered at the country level to account for serial correlation within countries.

4.8 Diagnostic Tests

To ensure the reliability of the results, the study conducts several diagnostic tests.

Table 5

Diagnostic Tests

Test	Purpose	Expected decision
Descriptive statistics	Summarizes the distribution of variables	Report mean, standard deviation, minimum and maximum
Correlation matrix	Checks preliminary relationships among variables	Avoid very high correlations among regressors
Variance inflation factor	Tests multicollinearity	VIF below 10 is acceptable
Hausman test	Chooses between fixed effects and random effects	Significant result supports fixed effects
Breusch-Pagan test	Tests heteroskedasticity	Use robust standard errors if significant
Wooldridge test	Tests serial correlation in panel data	Use clustered standard errors if significant
Unit root test	Checks stationarity where necessary	Variables should be stationary or transformed
Robustness test	Confirms stability of results	Use alternative dependent variables

4.9 Robustness Checks

The study performs robustness checks to confirm whether the findings are stable across alternative model specifications and variable measurements. First, the study replaces non-performing loans with bank Z-score as an alternative measure of banking risk. Since higher Z-score indicates greater stability, the expected sign of digital lending may differ from the NPL model. Second, the study uses capital adequacy ratio as another dependent variable. This tests whether digital lending affects the capital strength of banking systems. Third, the study estimates the model using lagged digital lending intensity. This helps reduce concerns about reverse causality, since current banking risk may also influence digital lending activity. Fourth, the study may replace IFRS adoption with the disclosure index if annual report data are available. Fifth, the study may split the sample into developed and emerging economies to examine whether the effect of digital lending differs across institutional environments.

4.10 Ethical Considerations

The study relies on publicly available secondary data and does not involve human participants. Therefore, it does not require direct ethical approval for primary data collection. However, the

study maintains research integrity by ensuring that data sources are properly acknowledged, variables are clearly defined, and results are reported transparently.

If annual reports are used to construct a disclosure index, the coding process should be documented clearly. To improve reliability, coding rules should be applied consistently across banks and countries. Where possible, a second coder may be used to confirm disclosure scores and reduce subjective bias.

5. Results and Discussion

5.1 Introduction

This section presents the estimated results on the relationship between digital lending intensity, accounting disclosure quality, banking risk, financial intermediation, and macroeconomic stability. The analysis follows the methodology described in Section 4 and is based on a proposed country-year panel dataset covering the period 2015–2023. The results are organized into five parts. First, descriptive statistics are presented to summarize the main characteristics of the dataset. Second, the correlation matrix is discussed to show the preliminary relationships among the variables. Third, the baseline regression results are presented to examine the effect of digital lending on banking risk. Fourth, the moderating role of accounting disclosure quality is examined. Finally, additional models are presented for financial intermediation, macroeconomic stability, and robustness checks.

Note: The numerical results below are illustrative estimated values for manuscript drafting. They should be replaced with actual results after collecting and analyzing the real dataset.

5.2 Descriptive Statistics

Table 6

Descriptive Statistics

Period: 2015–2023

Variable	Observations	Mean	Standard deviation	Minimum	Maximum
NPL	396	6.42	4.18	0.85	23.60
Bank Z-score	396	13.74	7.82	2.10	42.50
Capital adequacy	372	17.86	4.91	8.70	31.40
Digital lending/GDP	396	0.84	1.36	0.01	7.90
IFRS adoption	396	0.76	0.43	0.00	1.00
GDP growth	396	3.21	3.74	-9.80	12.40
Inflation	396	5.67	6.93	-1.20	44.30
Unemployment	396	7.91	5.16	1.20	29.80
Private credit/GDP	396	72.45	45.32	8.60	211.70
Regulatory quality	396	0.18	0.91	-1.82	2.03
Rule of law	396	0.12	0.96	-1.67	1.92

The descriptive statistics show that the average non-performing loan ratio is 6.42%, with a standard deviation of 4.18. This indicates that banking risk varies substantially across countries and years. The minimum NPL value is 0.85%, while the maximum is 23.60%, suggesting that some countries experienced significant credit-quality problems during the study period. The average bank Z-score is 13.74, indicating moderate banking stability across the sample. However, the wide range between 2.10 and 42.50 shows that banking stability differs considerably across countries. Capital adequacy has a mean of 17.86%, suggesting that the average banking system in the sample maintains capital levels above common regulatory minimums. Digital lending intensity has a mean of 0.84% of GDP, with a maximum of 7.90%. This suggests that digital lending remains relatively small compared with total economic output, but it is growing unevenly across

countries. The relatively high standard deviation indicates that some countries have much more developed digital lending markets than others. The mean IFRS adoption value is 0.76, indicating that about 76% of the country-year observations are associated with IFRS adoption or permission. This suggests that most countries in the sample operate within relatively strong financial reporting environments.

5.3 Correlation Analysis

Table 7

Correlation Matrix

Estimated values

Variable	NPL	DLGDP	IFRS	GDPG	INF	UNEMP	PCGDP	REGQ	ROL
NPL	1.000								
DLGDP	0.214	1.000							
IFRS	-0.186	0.291	1.000						
GDPG	-0.327	0.118	0.074	1.000					
INF	0.298	-0.064	-0.121	-0.236	1.000				
UNEMP	0.351	-0.089	0.048	-0.284	0.172	1.000			
PCGDP	-0.142	0.377	0.331	0.096	-0.211	-0.167	1.000		
REGQ	-0.263	0.318	0.452	0.146	-0.304	-0.198	0.421	1.000	
ROL	-0.281	0.295	0.438	0.139	-0.289	-0.214	0.407	0.762	1.000

The correlation matrix shows that digital lending intensity is positively correlated with non-performing loans. This provides preliminary evidence that higher digital lending activity may be associated with higher banking risk. However, the correlation is moderate, suggesting that the relationship should be examined further using multivariate regression. IFRS adoption is negatively correlated with NPL, indicating that stronger accounting disclosure environments may be associated with lower banking risk. GDP growth is also negatively correlated with NPL, which is consistent with the expectation that stronger economic performance improves borrowers' repayment capacity. Inflation and unemployment are positively correlated with NPL, suggesting that macroeconomic instability may increase banking risk. Regulatory quality and rule of law are negatively correlated with NPL, implying that stronger institutional environments may reduce credit risk.

The correlation between regulatory quality and rule of law is relatively high at 0.762. This suggests potential multicollinearity if both variables are included in the same regression model. Therefore, the models should include them carefully, or use one at a time as a robustness check.

5.4 Baseline Regression: Digital Lending and Banking Risk

Table 8

Baseline Regression: Digital Lending and Banking Risk

Dependent variable: NPL ratio

Variables	Model 1: Pooled OLS	Model 2: Country FE	Model 3: Country and Year FE
Digital lending/GDP	0.482**	0.391**	0.336*

	(0.197)	(0.176)	(0.181)
GDP growth	-0.214***	-0.187***	-0.162**
	(0.061)	(0.058)	(0.064)
Inflation	0.073**	0.058*	0.049*
	(0.031)	(0.030)	(0.028)
Unemployment	0.286***	0.241***	0.219**
	(0.082)	(0.079)	(0.086)
Private credit/GDP	-0.018**	-0.014*	-0.011
	(0.008)	(0.008)	(0.009)
Regulatory quality	-0.947***	-0.731**	-0.604*
	(0.312)	(0.341)	(0.356)
Constant	7.832***	6.941***	6.218***
	(0.913)	(0.884)	(0.902)
Country fixed effects	No	Yes	Yes
Year fixed effects	No	No	Yes
Observations	396	396	396
R-squared	0.284	0.417	0.462

*Notes: Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.*

Table 8 presents the baseline regression results. The coefficient of digital lending/GDP is positive and statistically significant across the three model specifications. In Model 1, the coefficient is 0.482 and significant at the 5% level. In Model 2, after controlling for country fixed effects, the coefficient decreases to 0.391 but remains significant at the 5% level. In Model 3, after including both country and year fixed effects, the coefficient is 0.336 and significant at the 10% level. These results suggest that higher digital lending intensity is associated with higher banking risk, measured by non-performing loans. The decline in coefficient size after introducing fixed effects indicates that part of the relationship is explained by country-specific characteristics and global yearly shocks. However, the continued significance of the coefficient suggests that digital lending remains relevant to banking risk even after controlling for these factors. The control variables generally show the expected signs. GDP growth is negatively associated with NPL, suggesting that stronger economic growth reduces banking risk. Inflation and unemployment are positively associated with NPL, indicating that macroeconomic instability and labor-market weakness increase credit risk. Regulatory quality is negatively associated with NPL, suggesting that stronger regulation reduces banking risk.

Therefore, Hypothesis 1 is supported.

5.5 Moderating Effect of Accounting Disclosure Quality

Table 9

Moderating Effect of Accounting Disclosure Quality

Dependent variable: NPL ratio

Variables	Model 1	Model 2
Digital lending/GDP	0.512**	0.476**
	(0.213)	(0.204)
IFRS adoption / disclosure quality	-0.684**	-0.591*
	(0.332)	(0.348)

Digital lending × IFRS adoption	-0.278**	-0.246*
	(0.137)	(0.142)
GDP growth	-0.174***	-0.159**
	(0.058)	(0.063)
Inflation	0.052*	0.047*
	(0.029)	(0.027)
Unemployment	0.232***	0.218**
	(0.081)	(0.085)
Private credit/GDP	-0.013*	-0.010
	(0.008)	(0.009)
Regulatory quality	-0.692**	-0.511*
	(0.319)	(0.304)
Rule of law	No	-0.386
		(0.291)
Country fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	396	396
R-squared	0.481	0.493

Notes: Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 9 presents the results for the moderating role of accounting disclosure quality. The coefficient of IFRS adoption is negative and statistically significant, indicating that countries with stronger accounting disclosure environments tend to have lower banking risk. This supports Hypothesis 2. The interaction term between digital lending/GDP and IFRS adoption is negative and statistically significant. This is the key result of the moderation analysis. It indicates that accounting disclosure quality weakens the positive relationship between digital lending and banking risk. In other words, digital lending is less likely to increase banking risk in countries with stronger financial reporting and disclosure environments. This finding supports the central argument of the study. Digital lending may increase banking risk when it grows without adequate transparency, risk disclosure, and expected credit loss recognition. However, when accounting disclosure quality is strong, digital lending data are more likely to be reflected in credit risk reporting, impairment models, risk governance systems, and supervisory monitoring. Therefore, Hypothesis 3 is supported.

5.6 Digital Lending and Financial Intermediation

Table 10

Digital Lending and Financial Intermediation

Dependent variable: Private credit to GDP

Variables	Model 1	Model 2
Digital lending/GDP	2.418***	2.106**
	(0.782)	(0.846)
IFRS adoption / disclosure quality	4.762**	3.985*
	(2.173)	(2.286)
Digital lending × IFRS adoption	1.384*	1.217*
	(0.741)	(0.716)
GDP growth	0.396**	0.352*
	(0.184)	(0.191)
Inflation	-0.218**	-0.196*
	(0.103)	(0.107)
Unemployment	-0.681**	-0.624**
	(0.276)	(0.289)
Regulatory quality	6.214***	4.872**
	(1.904)	(2.083)
Rule of law	No	3.126
		(2.147)
Country fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	396	396
R-squared	0.521	0.537

Notes: Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 10 reports the results for financial intermediation. The coefficient of digital lending/GDP is positive and statistically significant in both models. This suggests that digital lending contributes to financial deepening by increasing private credit to GDP. The result supports the argument that digital lending expands access to credit and complements traditional financial intermediation. Digital platforms may reduce transaction costs, improve borrower screening, and reach underserved households and firms. Therefore, digital lending can increase the supply of credit in the economy. The interaction term between digital lending and IFRS adoption is also positive and significant. This suggests that the financial intermediation benefits of digital lending are stronger in countries with higher accounting disclosure quality. This may be because stronger disclosure environments increase trust, improve transparency, and support more sustainable credit expansion.

Therefore, Hypothesis 4 is supported.

5.7 Macroeconomic Stability Results

Table 11

Macroeconomic Stability Regression

Dependent variables: Bank Z-score and credit-to-GDP stability

Variables	Model 1: Bank Z-score	Model 2: Credit-to-GDP stability
Digital lending/GDP	-0.418* (0.231)	-0.276 (0.198)
IFRS adoption / disclosure quality	1.926** (0.812)	0.814* (0.463)
Digital lending × IFRS adoption	0.337* (0.196)	0.281* (0.158)
GDP growth	0.286*** (0.092)	0.173** (0.081)
Inflation	-0.104** (0.047)	-0.087** (0.041)
Unemployment	-0.219** (0.092)	-0.134* (0.074)
Private credit/GDP	0.031** (0.014)	0.018* (0.010)
Regulatory quality	1.214** (0.531)	0.762** (0.347)
Country fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	396	396
R-squared	0.446	0.389

Notes: Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 11 presents the macroeconomic stability results. In Model 1, where bank Z-score is the dependent variable, the coefficient of digital lending/GDP is negative and significant at the 10% level. Since a higher Z-score indicates greater banking stability, this result suggests that digital lending may reduce banking stability when disclosure quality is weak. However, the interaction term between digital lending and IFRS adoption is positive and significant. This indicates that accounting disclosure quality helps reduce the destabilizing effect of digital lending. In other words, countries with stronger disclosure systems are better able to manage the macro-financial risks associated with digital lending.

The results also show that GDP growth and regulatory quality are positively associated with bank stability, while inflation and unemployment are negatively associated with stability. This is consistent with the view that macroeconomic strength and regulatory quality support financial stability.

Therefore, Hypothesis 5 is supported.

5.8 Robustness Test

Table 12

Robustness Test Using Alternative Banking Risk Measures

Variables	Model 1: Bank Z-score	Model 2: Capital adequacy	Model 3: NPL with one-year lag
Digital lending/GDP	-0.391* (0.218)	-0.214 (0.174)	0.298* (0.159)

IFRS adoption disclosure quality	/ 1.784**	0.926*	-0.514*
	(0.791)	(0.536)	(0.304)
Digital lending × IFRS adoption	0.314*	0.182	-0.221*
	(0.181)	(0.129)	(0.121)
GDP growth	0.271***	0.118*	-0.142**
	(0.087)	(0.071)	(0.059)
Inflation	-0.096**	-0.041	0.044*
	(0.045)	(0.036)	(0.026)
Unemployment	-0.205**	-0.067	0.194**
	(0.089)	(0.061)	(0.081)
Private credit/GDP	0.028**	0.012	-0.009
	(0.013)	(0.009)	(0.008)
Regulatory quality	1.106**	0.684*	-0.472*
	(0.508)	(0.361)	(0.278)
Country fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	396	372	352
R-squared	0.438	0.361	0.427

Notes: Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 12 reports the robustness tests. In Model 1, digital lending/GDP is negatively associated with bank Z-score, which confirms the baseline result that digital lending may increase banking risk. Since higher Z-score represents greater stability, the negative coefficient suggests that digital lending may reduce bank stability when not properly governed. In Model 2, digital lending/GDP has a negative but insignificant relationship with capital adequacy. This suggests that the direct effect of digital lending on bank capital strength may be weaker than its effect on credit risk. In Model 3, where NPL is measured with a one-year lag, digital lending remains positively associated with banking risk. This suggests that the effect of digital lending on credit risk may persist over time. The interaction term remains negative, supporting the moderating role of accounting disclosure quality. Overall, the robustness tests confirm the main findings.

5.10 Discussion of Findings

The findings provide evidence that digital lending has both beneficial and risky implications for financial systems. On the one hand, digital lending appears to support financial intermediation by increasing private credit to GDP. This suggests that digital lending can expand access to finance and deepen credit markets. This finding is consistent with the view that fintech can reduce information asymmetry, improve credit allocation, and reach underserved borrowers. On the other hand, the results suggest that digital lending may increase banking risk. The positive relationship between digital lending intensity and non-performing loans indicates that rapid digital credit expansion may expose financial systems to repayment problems, borrower over-indebtedness, and model risk. Digital lending systems may approve loans faster than traditional lending systems, but speed and convenience may also weaken credit discipline if not supported by strong risk governance. The moderating role of accounting disclosure quality is the central finding of the study. The negative interaction between digital lending and IFRS adoption shows that disclosure quality weakens the risk-enhancing effect of digital lending. This means that digital lending is not necessarily harmful by itself. Its effect depends on whether institutions and countries have strong disclosure, governance, and risk-reporting frameworks.

The findings also suggest that accounting disclosure quality contributes to macroeconomic stability. Stronger disclosure improves transparency, supports earlier recognition of expected credit losses, and allows investors and supervisors to identify emerging risks. In this way, accounting disclosure functions not only as a reporting mechanism but also as a financial stability tool. Overall, the results support the paper's central argument: digital lending data should be integrated into accounting disclosure and banking risk frameworks. Digital lending data should not remain isolated within credit-scoring systems. Instead, they should inform IFRS 9 expected credit loss models, IFRS 7 risk disclosures, supervisory reporting, bank risk dashboards, and macroprudential monitoring.

6. Conclusion, Implications, Limitations and Future Research

6.1 Conclusion

This study examined the integration of digital lending data into accounting disclosure and banking risk frameworks, focusing on implications for financial intermediation and macroeconomic stability. Using a proposed country-year panel framework for 2015–2023, the study analyzed the relationship between digital lending intensity, accounting disclosure quality, banking risk, financial intermediation, and financial stability. Digital lending intensity was measured as digital lending volume scaled by GDP, while banking risk was measured mainly by non-performing loans. Accounting disclosure quality was proxied by IFRS adoption or a disclosure index based on expected credit loss disclosure, credit risk segmentation, digital lending exposure, model risk, and macroeconomic assumption reporting. The findings suggest that digital lending is significantly associated with banking risk. Higher digital lending intensity is linked to higher non-performing loans, implying that rapid digital credit expansion may increase risk when not supported by strong governance, disclosure, and supervision. This may occur because digital lending can expand credit quickly, rely on automated scoring systems, increase borrower debt accumulation, and expose lenders to model and data-quality risks.

The study also finds that accounting disclosure quality reduces banking risk and moderates the relationship between digital lending and banking risk. The negative interaction between digital lending intensity and IFRS adoption suggests that stronger disclosure quality weakens the risk-enhancing effect of digital lending. Thus, digital lending is not inherently destabilizing; its risk impact depends on the quality of financial reporting, expected credit loss recognition, risk disclosure, and supervisory oversight. The results further indicate that digital lending can deepen financial intermediation by increasing private credit to GDP, expanding credit access, reducing transaction costs, and improving credit allocation. However, digital lending may reduce bank stability when disclosure and governance systems are weak. Overall, the study concludes that digital lending data should not remain isolated within operational credit-scoring systems. Instead, they should be integrated into IFRS 7 risk disclosure, IFRS 9 expected credit loss estimation, bank risk dashboards, model validation, supervisory reporting, and macroprudential monitoring to support sustainable financial intermediation and macroeconomic resilience.

6.2 Theoretical Implications

This study contributes to theory in four ways. First, it extends information asymmetry theory by showing that digital lending changes the information structure of credit markets. While alternative borrower data can reduce information gaps between lenders and borrowers, it may also create new information gaps between financial institutions and external stakeholders, such as investors, auditors, regulators, and depositors. Therefore, accounting disclosure quality becomes important in making digital lending data, algorithms, and model assumptions more transparent. Second, the study contributes to agency theory by showing that digital lending can increase managerial risk-taking incentives. Because digital platforms allow rapid loan growth, managers may expand digital credit aggressively to increase revenue, market share, or institutional performance. Strong

accounting disclosure can reduce this agency problem by improving monitoring, accountability, and stakeholder visibility. Third, the study contributes to financial stability theory by positioning digital lending as both a financial intermediation tool and a macro-financial stability concern. Digital lending can support inclusion and credit deepening, but it can also increase systemic risk through rapid credit expansion, borrower leverage, model risk, and procyclical lending behavior. Fourth, the study contributes to accounting literature by linking IFRS-based disclosure and expected credit loss reporting to fintech credit data. It shows that digital lending data can improve credit risk disclosure and expected credit loss estimation when such data are reliable, auditable, and properly governed.

6.3 Practical Implications

The study has implications for banks, fintech lenders, auditors, investors, regulators, and accounting standard setters. For banks, digital lending data should be treated as enterprise risk data rather than only as operational credit-scoring inputs. Banks should integrate such data into credit monitoring, expected credit loss models, stress testing, risk appetite frameworks, and board-level risk reporting. For fintech lenders, the findings highlight the need for transparency, model governance, and data quality. Alternative data and algorithmic scoring systems should be explainable, validated, monitored, and accompanied by disclosure of material risks such as model risk, platform concentration, borrower segmentation, and third-party data dependence. For auditors, audit procedures should expand to assess the data and models used in digital lending. Auditors should evaluate whether digital lending data used in expected credit loss models are complete, reliable, traceable, and consistent with accounting assumptions. For investors, digital lending growth should not be viewed only as innovation or market expansion. It should be assessed alongside credit risk disclosure, provisioning quality, model governance, and concentration-risk reporting. For regulators, digital lending should be incorporated into prudential supervision and macroprudential monitoring. Regulators should require disclosure of material digital lending exposures, algorithmic credit-risk models, expected credit loss assumptions, and borrower concentration risks. For accounting standard setters, the study suggests the need for clearer guidance on the use of alternative digital credit data in expected credit loss estimation and financial instrument risk disclosure.

6.4 Policy Implications

The study offers several policy implications.

First, regulators should develop reporting requirements for digital lending exposures. Banks and regulated lenders should report digital lending volumes, borrower segments, loan maturity structures, default rates, credit scores, and platform concentrations. Second, supervisory authorities should require financial institutions to integrate digital lending data into expected credit loss models. Where alternative data are used for loan origination, they should also be assessed for relevance in credit monitoring, staging, impairment, and provisioning. Third, regulators should strengthen model-risk governance for digital lending. This should include model validation, explainability, bias testing, stress testing, documentation, and board oversight. Fourth, macroprudential authorities should monitor digital lending as part of financial stability surveillance. Indicators such as digital loan growth, borrower debt-stacking, delinquency migration, platform concentration, and credit tightening by algorithmic lenders can provide early warning signals of systemic risk. Fifth, disclosure regulations should require financial institutions to explain material risks arising from digital lending. This may include risks from alternative data, algorithmic underwriting, fintech partnerships, cybersecurity, third-party data providers, and operational technology infrastructure. Sixth, policymakers should balance innovation and stability. Digital lending should not be restricted unnecessarily because it can expand access to

finance and deepen financial intermediation. However, innovation must be supported by transparency, consumer protection, data governance, and prudential oversight.

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