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An integrated GRC approach to combating fraud in microloan services

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Abstract

This research aims to reduce fraud risks in Indonesian banks and non-bank financial institutions providing microloan services. The study employs data analytics and machine learning techniques using employee data from Bank X spanning 2017-2019 with samples of 28,004 workers (2017-2018) and 27,274 employees (2019). Confirmatory factor analysis and XGBoost predictive modelling are applied within the fraud triangle framework to identify critical fraud risk indicators related to employee pressure. An algorithmic approach categorizes personnel based on fraud risk ratings enabling the detection of potentially suspicious activities for proactive intervention. The analysis reveals that incorporating data analytics into governance, risk management and compliance (GRC) systems can accurately forecast fraud probability by focusing on factors associated with employee pressure and opportunities. This facilitates targeted fraud prevention solutions by integrating control mechanisms, risk processes and auditing standards. The predictive model provides valuable insights for policymakers to combat fraud by enhancing governance and risk management practices specific to microloans. This research concludes that the predictive model is a pragmatic decision-making tool for banks offering micro-loans. It mitigates dangers by detecting high-risk personnel and transactions. Integrating data analytics with robust GRC frameworks enables financial institutions to uphold integrity through proactive fraud monitoring and targeted preventive interventions tailored to identify risk profiles. The study offers an integrated technological organizational approach to protect microlending activities.

Keywords: Fraud prediction, Fraud triangle theory, Machine learning, Microloan services, Relationship manager, Risk management, XGBoost modelling.

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1. Introduction

Banks and Multi Financial Institutions (MFIs) help underprivileged populations achieve global financial inclusion and economic development. These organizations must manage credit and risk exposures effectively to survive and accomplish their social goals [1]. MFIs struggle to manage credit risk, resulting in non-performing loans and portfolio performance difficulties despite their significance [2]. MFIs' complicated customer base which includes microenterprises and people with little or no credit history makes credit risk management challenging. MFIs lack comprehensive credit scoring procedures and historical data, making creditworthiness evaluation difficult. Therefore, customers are more likely to default increasing the institution's credit risk. The sensitivity of microenterprises to economic shocks and swings increases MFI risk. Micro entrepreneurs may struggle to repay their loans during economic downturns or market volatility increasing the MFI's non-performing loans. MFIs need robust risk management methods since the COVID-19 epidemic caused a worldwide economic crisis highlighting microfinance customers' vulnerability to external shocks. Fraud threatens MFIs' finances and image in addition to economic issues [3]. Fraudulent actions including identity theft and loan diversion schemes cost the institution money and damage investor and customer trust.

Several studies have shown that data analytics and machine learning can improve fraud prediction. Perols, et al. [4] and Ikhsan, et al. [5] concluded that these technologies could dramatically improve fraud detection. Ikhsan, et al. [5] highlighted these technologies' role in assisting with internal audits. Singla and Jangir [6] emphasizes the significance of these tools in real-time financial data while Patil [7] offers a complete review of machine-learning approaches for fraud prediction in the insurance industry. These results provide credence to the concept that incorporating data analytics and machine learning into microloan services might enhance the accuracy of fraud prediction and risk grading. Meanwhile, a wide variety of research has applied XGBoost modelling to identify instances of fraud in various settings. According to their findings, Zhou, et al. [8] and Wang, et al. [9] discovered that XGBoost performed better than other models when it came to predicting fraud in the supply chain and credit transactions. According to Zopluoglu [10] XGBoost successfully spotted fraudulent activity in large-scale testing. In further investigating the use of XGBoost in detecting credit fraud, Meng, et al. [11] discovered that XGBoost performed well on both the original and balanced data sets when they examined the algorithm's possibility of detecting financial fraud. The findings of this research provide insight into the ability of XGBoost to detect fraudulent signs across various sectors.

This study strives to fill the knowledge gap about the effectiveness of predictive analytics and governance, risk management and compliance (GRC) frameworks for reducing fraud in microloan services. Supriyadi et al.'s previous studies in this field addressed this topic [12]. Further research is needed to optimize integrated GRC procedures in microloan operations to address the complexity caused by dependence on relationship managers and prevent fraud. The current study has focused chiefly on auditing techniques and financial procedures. However, more evaluation is required regarding the cultural integration and harmonization of GRC functions for risk management. Furthermore, the use of sophisticated data analytics and machine learning methods to forecast the likelihood of fraud based on employee activities and transactions has been restricted up to this point. Existing fraud prediction models lack adequate integration of critical components of the fraud triangle such as pressure, opportunity and reasoning that influence fraudulent behaviour. Boyle, et al. [13] suggest that the model could be enhanced by incorporating a broader capability dimension which includes rationalization and attitude.

The research questions of this study were to determine whether or not combining data analytics and machine learning can enhance fraud prediction and whether the predictive model can successfully classify people according to risk. Additionally, the research aims to determine which theories of the fraud triangle , namely opportunity, rationalization, and pressure have the most significant influence on the likelihood of fraud occurring in the microloan service process at microfinance institutions. Furthermore, this research seeks to identify data analytics models that can effectively predict fraud risks in the microloan service process based on variable inputs and red flags. Lastly, the research aims to formulate strategies for using data analytics in the GRC (Governance, Risk and Compliance) process to mitigate fraud risks in micro lending services. Therefore, the hypothesis developed is that it is predicted that improving governance, risk, and compliance (GRC) using data analytics can eliminate fraud threats in microloan services based on the arguments above and to answer the research question. This research included a literature review , methodology, the findings and discussion, a conclusion and references.

2. Literature Review

Fraud may manifest in several ways such as through misrepresentation, non-disclosure and exploitation of a position of financial trust [14]. General fraud charges introduced in many Australian jurisdictions have expanded the definition of fraud to include general dishonesty and the acquisition or loss of any kind. The charges have faced criticism for being broad and imprecise and relying on mental condition claims to penalize otherwise legal conduct [15]. Fraud can be caused by two types of actors, namely external actors and internal company actors. Fraud caused by external parties or outside the company is usually transactional, so losses can be significantly reduced when the company can manage them appropriately. Fraud from internal sources, such as gratification, manipulation of data or documents and corruption can be reduced by mapping the root cause of fraud events or seeing signs (red flags) of fraud that may arise. PWC [16] said internal fraud tends to be more challenging to predict and monitor, resulting in higher costs. Internal fraud also has additional repercussions such as loss of business or brand. Internal fraud is also considered potentially far more damaging than crimes committed externally. Fraud incidents often impact legal risk because there are civil or criminal claims against the company.

According to some of the most prominent hypotheses about fraud, several elements may contribute to its occurrence. The key elements that contribute to a rise in the amount of corruption [17] wage level [18] urbanization rate and globalization [17] include inefficient bureaucratic, administrative and political systems. On the other hand, according to Bhattacharyya and Hodler [19], some characteristics have been shown to limit the prevalence of corruption. These aspects include civic participation, press freedom and ethnic diversity. Ethnic diversity is one of the elements shown in other empirical investigations to have the potential to lessen the causes of corruption [20]. High economic development may also successfully lower levels of corruption [21, 22]. Current globalization can help reduce corruption particularly in poor countries Badinger and Nindl [23]. Glaeser and Saks [24] discovered through other empirical investigations that a relationship exists between more significant education levels and lower corruption levels. According to Anderson [25] there is a relationship between higher internet accessibility and use and lower overall levels of corruption.

Most previous studies reviewed negative perspectives on fraud that occurs in companies, industries and countries. Several researchers have linked it to economic growth. However, very few researchers discuss the positive perspective of fraud on economic growth. Gano-an and Chea [26] highlight fraud's negative and positive perspectives on economic growth. Gano-an and Chea [26] also discussed the positive side of corruption because not all researchers agree that the development of a country can only be achieved through government policies and bureaucracies that are not corrupt. The optimistic view of corruption is also discussed by Houston [27] who argues that corruption has positive effects which Sharma and Mitra [28] call efficient fraud.

Van Greuning, et al. [29] and Oluyombo and Olabisi [1] highlight the significance of a regulatory framework in managing risks linked to microfinance institutions or organizations. The need for a tiered strategy for regulation is brought to light by these findings. This approach should take into consideration the various kinds of microfinance institutions as well as the dangers that they face. According to Daher and Le Saout [30] microfinance institutions must take precautions to protect themselves against the danger of loan default and changes in the financial market. A complete review of the application of governance, risk and compliance (GRC) frameworks in businesses is presented by Makaš [31]. The author emphasizes the need for a mature and financially solid organizational structure to maintain the implementation of these frameworks. The findings of these studies together indicate that enterprise risk management (GRM) frameworks have the potential to assist microloan institutions in mitigating the risk of fraud. These frameworks provide a methodical approach to detecting, evaluating and managing risks and ensuring compliance with applicable laws and regulations.

Hence, effective Governance, Risk Management and Compliance (GRC) are crucial in combating fraud. This research highlights the GRC as an integrated and comprehensive approach to ensure ethical business behaviour and aligning strategy, processes and people with regulations and risk appetites (see Figure 1). It emphasizes the need for integrated GRC practices, organizational cultural implementation and harmonizing functions to achieve maximum efficiency and effectiveness. The GRC is an integrated set of many skills that lends organisations dependability in accomplishing their objectives, managing uncertainty and functioning with justice (see Figure 1) [32]. It also mentioned that the company has been well run so far and risk and compliance have been managed and going on for a long time. Therefore, in this case, the GRC was not new. However, many companies have not managed GRC practice and compliance well and are mutually supported to achieve the organization's goals.

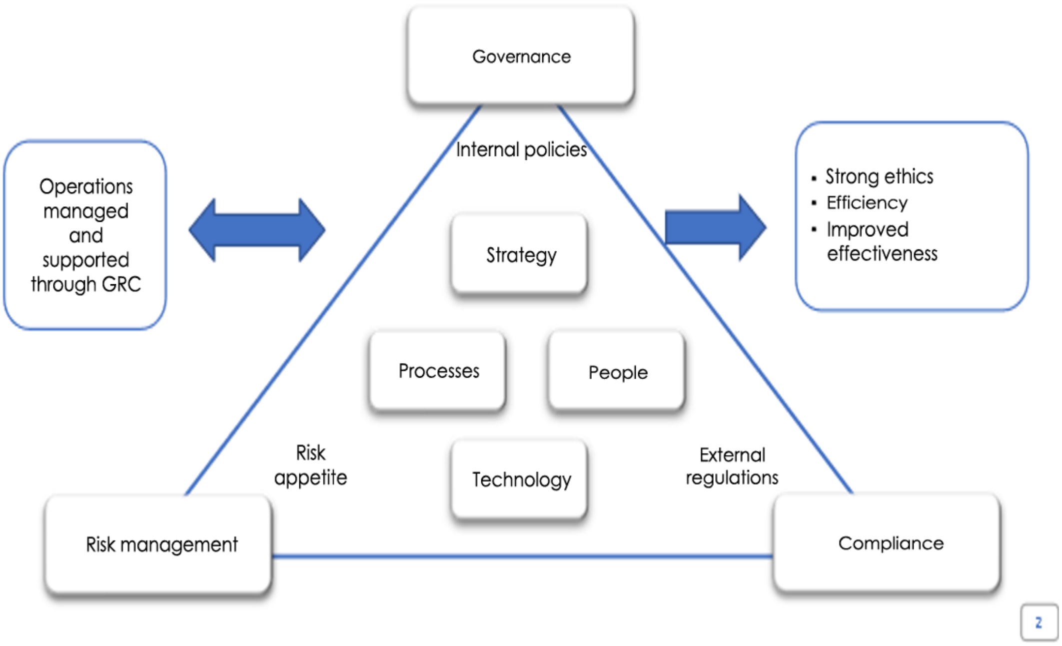

Figure 1.
The GRC framework.

According to Prowanta [33] GRC must have mandatory limits from external forces (regulations, laws, etc.), business models to achieve business goals, company objectives that must be achieved through business and operational strategies and processes and tolerance limits such as company values, tolerance limits and risk appetite in the Indonesian context. Siahaan, et al. [34] in GRC Forum Indonesia said that in today's era of fast-paced change, organizations must carry out governance, risk management, compliance functions and performance achievement activities. Furthermore, Siahaan, et al. [34] stated that the implementation of GRC needs to be improved to support the banks' and MFIs' transformation process and optimize business initiatives with risk prioritization. On the other hand, Anastasya and Noviyanti [35] examined the application of GRC in Indonesian micro banks and financial services company that serve microcredit showing that of the three concepts used, namely Governance Good Corporate Government (GCG), risk and compliance only risk significantly influence company performance, both financial and non-financial. Daniri and Roseline [36] concluded that all activities summarized to implement integrated GRC must be manifested in corporate culture. GRC must be implemented in the form of culture so that the company's human resources can implement GRC.

On the other hand, predictive analytics, mainly social media analytics have been recognized as a beneficial tool for identifying fraudulent applications for online microfinance loans [37]. This contrasts with predictive analytics alone which cannot identify fraudulent applications. The detection procedure for microloan fraud may be enhanced by using data mining techniques such as feature selection and representation [38]. This is especially significant in the case of microloan fraud. Credit risk assessment closely connected to fraud detection in micro-loans has also been proven successful in using machine learning approaches including ensemble and hybrid models [39]. Such strategies are beneficial. In addition, regression analysis has been suggested as a feasible approach to identifying fraudulent activity especially in the context of intricate data association patterns [40].

An increasing number of people agree that the best method to address fraud is to use an integrated strategy that merges GRC frameworks with predictive analytics. This method uses data from diverse sources such as loan applications, credit reports and social media to thoroughly understand each borrower's risk profile. This data may be used to make well-informed judgments on lending, including loan approval and determining the appropriate interest rate. One obstacle to this method is that microloan institutions often do not have the means to invest in advanced data analytics technologies. Microloan institutions may take many actions to enhance their use of data for fraud prevention. These phases include pinpointing the facts most relevant to fraud risk such as the borrower's financial history, work record and social media presence. Microloan institutions should prioritize safe and accessible data collection and storage and establish a governance structure to guarantee ethical and responsible data use. Microloan institutions may improve their ability to detect fraud and better manage risk by using data analytics tools to recognize patterns and trends associated with fraudulent activities.

Debates have arisen over the use of GRC frameworks and predictive analytics in fraud prevention due to possible adverse effects. According to the findings of the GRC Maturity Survey that was carried out in 2019 by the Open Compliance & Ethics Group (OCEG), just 14% of respondents had completely or significantly integrated GRC processes and technology. Meanwhile, 23% of respondents still have siloed GRC and the remaining does not have acceptable GRC maturity levels. However, the results of studies related to how GRC was integrated were conveyed by Vicente and Mira da Silva [41]. The implementation of GRC starts from the management oversight side to monitor activities and other technical levels that intersect between activities in the realm of policy management, risk management and audit management. This framework was fundamental to build complete integration and mutual support for the company's strategic achievements.

There is also a discussion over the cost-effectiveness of these instruments especially for microloan institutions that are on the smaller side. There is much complexity in the discussion of whether or not GRC frameworks and predictive analytics technologies are cost-effective for micro-learned institutions. In their respective studies, Mosley and Hulme [42] and Morduch [43] stress the potential for these instruments to boost the effect of microfinance organizations especially in alleviating poverty and reducing vulnerability. However, Cull, et al. [44] and Kaboski and Townsend [45] warn that the significant expenses associated with these technologies may restrict their efficacy particularly for institutions that are on the smaller side. Cull, et al. [44] further add that investors interested in maximizing profits can be less interested in institutions concentrating on the poorest clients further complicating the cost-benefit equation. Therefore, even though the long-term advantages of these instruments are readily apparent, the initial expenditure required to use them may provide a considerable obstacle for microloan institutions that are on the smaller side.

According to Morduch [43] microloan services can significantly affect both the provision of financial inclusion and the growth of the economy especially for borrowers with low incomes. On the other hand, they are susceptible to fraud which both external and internal players may commit [43]. Additionally, they are susceptible to fraud. Microfinance has been shown to have high payback rates and the capacity to eliminate poverty. This is applicable despite several obstacles. The necessity for innovation in microfinance has been brought to the forefront even more by the transition towards a financially feasible model [44]. Microfinance programs have investigated novel methods such as direct monitoring and regular payback schedules to guarantee high repayment rates. This is to address the issues that have been presented. This paper comprehensively analyses fraud prevention and risk mitigation within microloan services, encompassing banks and nonbank financial institutions. It endeavors to elucidate the underlying factors contributing to fraud, examine the impact of governance, risk and compliance (GRC) practices and evaluate fraud's potential advantages and disadvantages on economic growth. Moreover, the research aims to evaluate the viability of using data analytics and machine learning to predict fraud risks inherent in microloan services. It also aims to investigate the potential enhancement of fraud risk prediction within microloan services by integrating data analytics and machine learning. Additionally, the research assesses the efficacy of a 'fraudulent model' designed to identify individuals involved in fraud activities. Research endeavors to better understand fraud dynamics within microloan services and provide valuable knowledge for developing more effective prevention measures through these investigations.

3. Method

The Fraud Triangle Theory provides a framework for extracting and integrating data related to key risk indicators, including pressure, opportunity and rationalization elements. Representative training and testing datasets were selected from the acquired data to create and verify the XGBoost model which confidently estimates the risk of employee fraud. The prediction model underwent thorough and unbiased assessment using receiver operating characteristics (ROC), Gini coefficient and Kolmogorov-Smirnov statistical measures to ensure its robustness before being used to score actual instances. The model's advanced fraud detection skills were smoothly integrated into a comprehensive Governance, Risk, and Compliance (GRC) enhancement framework tailored to identify the bank's organizational weaknesses. This facilitated the creation of effective and outcome-oriented fraud prevention strategies focusing on specific problem areas to balance effectiveness and long-term viability. This study introduces a novel predictive fraud risk model that combines confirmatory component analysis with extreme gradient boosting (XGBoost) modelling. This new fraud prediction model integrates social identity features with fraud triangle variables to calculate the likelihood of wrong doing in sophisticated human-system interactions unlike previous models. The program incorporates advanced machine learning methods such as specialized predictive analytics to accurately examine employee statistics and identify high-risk people. This innovative computational method varies from traditional corporate audits and generalized financial control studies by using interpretable data science to identify individualized wrongdoing proactively. The goal is to provide advanced AI software that combines sociological insights, psychological research and technical skills to maintain integrity in distant workforces.

3.1. Research Design and Technique

The research encompasses several approaches to problem-solving based on data analytics first seeking to find widespread use in various sectors including the banking industry. In this analysis, data analytics is an iterative process that links numerous statistical approaches including sampling, model estimation, model prediction and evaluation to produce an integrated system. The goal of this system is to estimate fraud that might cause damage to the firm. The methodology used in this research was a combination of quantitative research methods. The quantitative analysis explains and measures the degree to which the independent variable influences the dependent variable. The degree of control in the form of varied goal opportunities, rationalization and pressure may be objectively described and measured using this analytical technique. The theoretical examination of the analysis was included in the review section devoted to the literature. At the same time, the conceptual framework was a condensed plan of the primary stages that the researcher went through to draw a conclusion on anything. The research also used operational variables such as the dependent variable and the independent variable further broken down into the variables of opportunity, rationalization and pressure. In the first stage, information related to the Indonesian Bank 'X' fraud was exploited. A technique was carried out in several locations and the outcomes were compared. This research used the XGBoost model to check the probability of someone committing fraud by first finding the most influential variables selected through the Confirmatory Factor Analysis (CFA) that cause someone to commit fraud. The results of CFA and XGBoost would be formulated for use in the GRC process to mitigate fraud in microloan services through the interview method.

3.2. Data Collection, Participants and Tools

The study used a variety of statistical software packages for advanced predictive modelling, created structured questionnaires for expert interviews, gained access to the bank's extensive databases and conducted detailed ethnographic observations of microloan operations. Automated machine learning algorithms gathered pertinent information from many personnel records and evaluated them to identify intricate misbehaviour patterns. Simultaneously, thorough discussions with experts in the field facilitated a clear interpretation of model indications and results by aligning them with real-world situations. The study technique combined computational analysis of fraud indicators with empirical insights from years of experience in microfinance. The integration of advanced technology and collective insights drove the development of the next-generation fraud risk framework through social engineering. The research was done and implemented intensively from early January 2017 to December 2019 involving activities including research preparation (*literature review*), proposal review, data collection and analysis processes and the preparation of reporting on research results conducted in Jakarta. The initial data collection was conducted through semi-structured interviews with selected stakeholders. Respondents have previous expertise in the microloan procedure at Bank 'X' and duties linked to that process. In addition, the author collected data, did some analysis and conducted tests using the Fraud Triangle Theory to identify red flag data pertinent to identifying employees who were committing fraud related to the Grand Theory .

The second stage was to get secondary data which was taken from private companies, governmental institutions or any other relevant published data. The primary aspects of investigating through interviews and observations were determined based on the data. In the first and second processes, key aspects were identified. The model or frame of mind developed through the first hypothesis was then modified. Finally, the relevant questionnaire was revised and adapted. The data used was internal data of bank 'X' attached to the whole number of the microloan RM. The research data in 2017-2018 covered 28,004 workers while the data in 2019 showed 27,274 workers. The data was divided into four categories: demographic data, career data, performance data and transaction data . The limitations of understanding fraud in microloan services activities in this research were fictitious credit, masks, patches and delays in loan instalment deposits. The data in 2017-2018 was made in two windows: training data (observation) covering 16,494 workers and testing data (data performance) consisting of 4,122 workers in order to process data using the XGBoost method. The red flag data attached to these four categories and their influence on fraud were mapped according to the components of the Fraud Triangle theory.

4. Results and Discussion

The predictive analysis of fraud using the second order CFA and XGBoost methods enables financial institutions to address potential fraud risks proactively. The model can identify high-risk individuals and transactions allowing financial institutions to take preventive measures and minimize potential losses due to fraud. They can implement targeted measures to prevent fraud and safeguard their assets and reputation by identifying high-risk individuals and transactions. It is revealed that the pressure factor of the Triangle Fraud Theory was the dominant factor in microloan services and it also showed that moving user/employee rotation was the dominant factor using the second order CFA method. In this research, the authors continued implementing the predictive analysis of fraud by using the XGBoost method. The authors identified the threshold which is referred to as a cutoff value that separates low-risk and high-risk individuals or transactions. It was a critical decision point to determine that the microloan Relationship Manager (RM) is a potential fraud risk. The threshold value was usually set based on business requirements, risk appetite and the trade-off between false positives and false negatives. False positives occur when a low-risk individual is classified as high-risk while false negatives occur when a high-risk individual is classified as low-risk. The authors calculated the fraud risk score for each microloan RM.

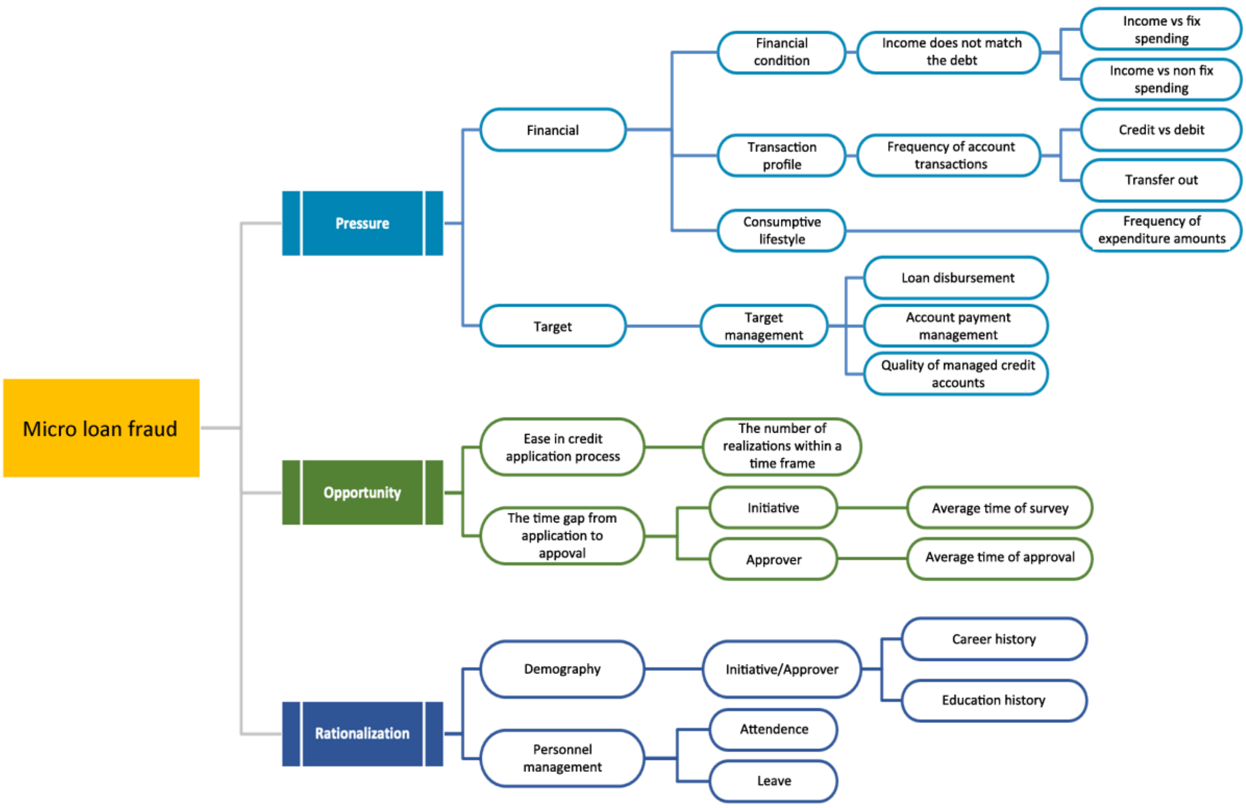

Figure 2.
Red flags in the micro loan process.

Figure 2 shows how microloan red flags relate to pressure, opportunity and reasoning in the fraud triangle hypothesis. It shows 12 critical demographic, career, performance and transaction data factors. Employee and loan application profile signals may forecast fraud risk with strong computer models. Length of service, positioning in high-risk zones and consumer complaints increase fraud pressure. A lack of dual control and uneven Standard Operating Procedures (SOPs) increase misbehavior chances. High turnover normalizes misconduct and erodes ethical standards. The methodology identifies microloan lifecycle weaknesses at the granular level rather than broadly. This precision allows focused interventions like staff coaching, digital systems and audits. High-risk indicators use mixed-methods fraud triangle triangulation in the micro context to ensure relevance. The concept focuses on four fraud typologies to identify predictive factors for appropriate findings. Laudable is the addition of demographic and transactional factors including individual peculiarities, societal pressures and institutional failings. The figure suggests layering analytical complexity into layers to expand risk sources and mitigation capabilities. It provides essential infrastructure for sophisticated models to protect microloan services from fraud and cultural toxicity. The risk indicators and mapping method might be applied to other financial sectors subject to human discretion. It allows for further study of data science and institutional integrity ethics.

4.1. Model Implementation and Validation

The model incorporated various indicators related to pressure, opportunity and rationalization and it estimated the overall fraud risk of each individual through the Confirmatory Factor Analysis (CFA) method. Moreover, the CFA helped to identify latent variables (e.g., pressure , opportunity and rationalization) that were not directly observed but influenced the observable indicators (e.g., specific behaviours or traits) related to fraud risks. Once the fraud risk scores were calculated, they were classified into different risk categories. The threshold value was identified in the first step. The RMs with scores above the threshold was classified as high-risk while those below the threshold were classified as low-risk. The risk classification helped financial institutions focus on high-risk individuals and transactions as they tended to be involved in fraud activities. This categorization enabled the institution to prioritize its fraud detection and prevention efforts for this high-risk group. In this way, financial institutions can effectively leverage the predictive power of the second order CFA Micro RM fraud risk model to identify potential fraud risks and take proactive measures to mitigate them. Moreover, it helps in allocating resources better, reducing false alarms and enhancing the overall effectiveness of the fraud prevention system.

The loading factor of each indicator against the latent variable was calculated to further validate the model (see Table 1). The result shows that out of 28 indicators, 23 are significant at α=0.05 indicating that these indicators are essential for assessing fraud risk in microloan RMs. Among the three latent variables, pressure significantly influences the risk of fraud committed by micro RMs followed by opportunity and rationalization.

Table 1.
Value of the loading factor.

Latent variables	Indicators	Estimate	Std. err	z-value	P(>|z|)
Pressure	P1	0.6	0.0	72.4	0.0
Pressure	P2	0.4	0.0	77.9	0.0
Pressure	P3	1.9	0.0	94.3	0.0
Pressure	P4	0.8	0.0	92.5	0.0
Pressure	P5	1.5	0.0	100.6	0.0
Pressure	P6	0.7	0.0	90.9	0.0
Pressure	P7	0.5	0.0	96.3	0.0
Pressure	P8	0.0	0.0	80.2	0.0
Opportunity	O1	2.6	0.0	101.6	0.0
Opportunity	O2	0.7	0.0	101.3	0.0
Opportunity	O3	0.4	0.0	101.5	0.0
Opportunity	O4	0.4	0.0	100.7	0.0
Opportunity	O5	0.4	0.0	101.4	0.0
Opportunity	O6	0.5	0.0	101.5	0.0
Opportunity	O7	0.2	0.0	101.6	0.0
Opportunity	O8	0.3	0.0	101.5	0.0
Opportunity	O9	0.0	0.0	101.5	0.0
Opportunity	O10	0.0	0.0	-2.4	0.0
Rationalization	R1	0.0	0.0	33.0	0.0
Rationalization	R2	0.0	0.0	1.5	0.1
Rationalization	R3	0.2	0.0	101.5	0.0
Rationalization	R4	0.2	0.0	101.5	0.0
Rationalization	R5	0.0	0.0	101.5	0.0

The result shows that 23 indicators are significant, the sources that make up the three factors of triangle fraud. This was shown by the p-value of each indicator which was less than the significant level with α=0.05. A factor analysis using the Confirmatory Factor Analysis (CFA) method shows that pressure is the most significant factor loading variable. Thus, it can be concluded that pressure has the most significant influence on fraud committed by microloan RMs. Meanwhile, when viewed from each parameter and indicator, the most significant value was 'working unit' and outstanding loan. It means that the variables that were very influential on the model were the parameters of moving users and outstanding loans. This reveals that pressure, opportunity and rationalization significantly influence fraud risks committed by microloan RMs.

4.2. Model Evaluation and Practical Implications

The analysis was followed by Confirmatory Factor Analysis (CFA) to ensure that significant variables were used to measure the risk of orderly fraud. Nevertheless, it was necessary to test how much Construct Reliability (*CR*) there was beforehand which can be formulated as follows:

$$CR = \frac{\left[\sum_{i=1}^{n} L_i\right]^2}{\left[\sum_{i=1}^{n} L_i\right]^2 + \left[\sum_{i=1}^{n} e_i\right]}$$

The construct reliability value of the second order, the risk of orderly fraud was 0.512. It means that the risk of orderly fraud has good reliability. After getting the path diagram, the model identification was implemented. The model identification was implemented before the estimation stage of the CFA model. The number of parameters to be estimated (*t*) was 3 while the number of variances and covariance between manifest variables (*s*) was 41. This shows that the over-identified model was due to the value of $t < s$. Thus, this over-identified model is needed to obtain the estimated value of the parameters formed in the CFA model. The estimate used in this research was the maximum probability estimation. Model testing aims to see unidimensional indicator variables in explaining latent variables with hypotheses and model suitability criteria shown in Table 2.

Table 2
Validity and reliability model.

No.	Statistics	Result	Criteria	Description
1	Minimum fit function chi-square ($\chi 2$)	221.882 (p_value=0.0)	p_value > 5%	Not fit
2	RMSEA	0.07	< 0.08	Fit
3	RMR	0.04	<= 0.1	Fit
4	SRMR	0.04	<= 0.1	Fit
5	GFI	1.0	>= 0.9	Fit
6	AGFI	1.0	>= 0.9	Fit
7	NFI	0.9	>= 0.9	Fit
8	NNF	0.9	>= 0.9	Fit
9	CFI	0.9	>= 0.9	Fit
10	IF	0.9	>= 0.9	Fit
11	RFI	0.9	>= 0.9	Fit
12	PNFI	0.8	>= 0.9	Not fit

It can be seen that some metrics have a good fit (RMSEA, RMR, SRMR, GFI, AGFI, NFI, NNFI, CFI, IFI and RFI) while PNFI does not meet the fit criteria i.e., less than 0.9 (see Table 2) based on the results of model evaluation using these fit indices. This indicates that the model has a reasonable overall fit but may need refinement to improve its parsimony. The model evaluation and validation help in assessing the reliability and robustness of the fraud risk prediction model. Therefore, it can be concluded that it is necessary to implement a fraud monitoring system that regularly assesses microloan RMs' activities and transactions by focusing on high-risk individuals and transactions to identify suspicious patterns or behaviours that might indicate fraud activities. In the provided analysis, several fit indices and statistical metrics are used to evaluate the second order CFA Micro RM fraud risk model.

- Minimum fit function chi-square ($\chi 2$): In this case, a p-value more significant than 5% is considered acceptable. However, the p-value is less than 5% suggesting that the model does not fit the data well.
- Root Mean Square Error of Approximation (RMSEA): A RMSEA value of 0.07 indicates a reasonably good fit as it is less than the cutoff value of 0.08.
- Root Mean Square Residual (RMR): 0.04 is considered acceptable as it is less than or equal to 0.1.
- SRMR Standardized Root Mean Square Residual (SRMR): 0.04 or less is considered a good fit.
- Goodness-of-Fit Index (GFI): A GFI value of 1.0 indicates a perfect fit and the GFI value here is equal to 1.0 suggesting a good fit.
- Adjusted Goodness-of-Fit Index (AGFI): An AGFI value of 1.0 is considered a good fit.
- Normed Fit Index (NFI): NFI value of 0.9 or greater is considered a good fit. In this analysis, the NFI is 0.9.
- Non-Normed Fit Index (NNFI) or Comparative Fit Index (CFI): NNFI value of 0.9 or greater is considered a good fit.
- Incremental Fit Index (IFI): An IFI value of 0.9 or greater is considered a good fit.
- Relative Fit Index (RFI): A RFI value of 0.9 or greater is considered a good fit.
- Parsimony Normed Fit Index (PNFI): A PNFI value of 0.8 or greater is considered a good fit but less than 0.9.

The result of model evaluation reveals that some metrics have a good fit (RMSEA, RMR, SRMR, GFI, AGFI, NFI, NNFI, CFI, IFI and RFI) while PNFI does not meet the fit criteria (less than 0.9). This indicates that the model has a reasonable overall fit but may need refinement to improve its parsimony. The model evaluation and validation help in assessing the reliability and robustness of the fraud risk prediction model. Therefore, the authors conclude that implementing a fraud monitoring system is necessary to regularly assess microloan RMs' activities and transactions by focusing on high-risk individuals and transactions to identify suspicious patterns or behaviours that might indicate fraudulent activities. If the model performs well, it can be used to predict the fraud risk of RMs in microloan services and help make decisions regarding fraud prevention and mitigation strategies. However, further analysis and adjustments may be needed to enhance its predictive capabilities if the model shows weaknesses or a poor fit.

4.3. Model Validation and Performance Metrics

Figure 3 shows how the ROC metric, Gini coefficient and Kolmogorov-Smirnov test verify this research's prediction fraud risk model. The model's consistent values across training, testing and validation datasets show its accuracy in detecting fraud. The model's strong ROC values of 80.17%, 77.12% and 29.98% show its accuracy in reducing false positives and negatives. This also shows that the strategy works across samples. The model's Gini coefficients of 46.91%, 42.93% and 44.14% show its ability to distinguish high- and low-risk groups. The Kolmogorov-Smirnov measurements demonstrate that risk ratings match fraud probabilities. Multifaceted validation shows that financial institutions can trust this platform for security and efficiency. Prevent losses by detecting suspect employee activities and transactions based on risk indicators. The model may support a daily diagnosis. It may help optimize audit resource allocation by highlighting risky locations. The methodology may also help managers balance expansion and management. Institutions may communicate their governance strengths to investors through risk visualizations. An extensive fraud likelihood tool assessment gives confidence in implementing predictive measures to maintain integrity and improve financial access. Data-driven risk insights help institutions maintain microfinance.

	Data training	Data testing	Data validation
Parameters	Value	Value	Value
ROC	80.17%	77.12%	79.98%
Gini	46.91%	42.93%	44.14%
Kolmogorov - Smirnov	60.34%	54.34%	59.95%

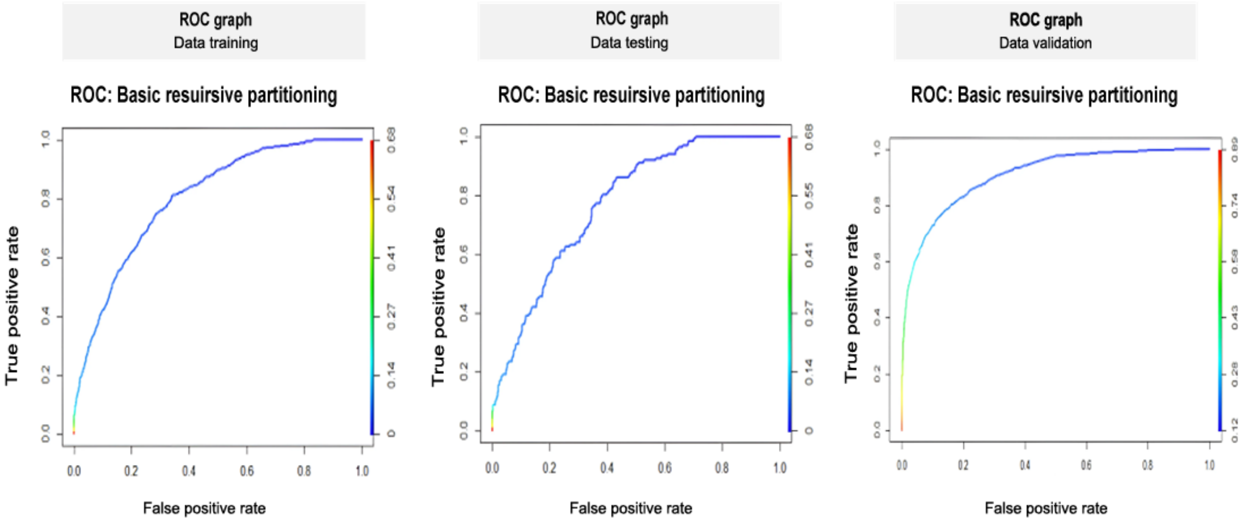

Figure 3.
Prediction model.

The authors can address the fact that integrating data analytics and machine learning can improve the prediction of fraud risks in microloan services based on the results of the analysis. The analysis presented in the article supports this hypothesis. The research used data analytics and machine learning techniques, specifically the second order CFA Micro RM fraud risk model to predict fraud risks in microloan services. The model incorporated various indicators such as pressure , opportunity and rationalization to measure the risk of fraud committed by the micro RM. The model evaluation shows that specific fit indices such as RMSEA, RMR, SRMR, GFI, AGFI, NFI, NNFI, CFI, IFI and RFI indicate a good fit. This reveals that integrating data analytics and machine learning can effectively predict fraud risks in microloan services.

However, it should be noted that the PNFI fit index did not meet the criteria indicating a potential room for improvement in model parsimony. In a nutshell, the research findings support the first hypothesis that integrating data analytics and machine learning can enhance the prediction of fraud risks in microloan services, providing valuable insights for fraud prevention and risk mitigation in financial institutions offering microloans. The authors apply the model built with the Decision Tree method to XGBoost to answer the second hypothesis. The result shows they can effectively rank RM workers based on their fraud risk scores. The model seems to differentiate between high and low-risk individuals as seen from the distinct score distributions between the top 10 high and low scores. However, to assess the model's predictive capability more comprehensively, the research provides additional information on the model's performance metrics such as accuracy, sensitivity, specificity, precision, recall, F1-score and area under the ROC curve Area Under Curve (AUC). These metrics will provide a more accurate assessment of the model's ability to predict someone committing fraud. The research's findings support the second hypothesis that the 'Fraudulent Model' can somewhat predict someone committing fraud as it effectively ranks individuals based on their risk scores (see Table 3).

Table 3.
List of the top 10 high and 10 low scores of RM workers.

No.	Region	Branch	Position	Name	Score
1	RG06	0B4176	RM	R01	0.86
2	RG25	0B3870	Junior associate RM	H02	0.86
3	RG24	0B3541	RM	P03	0.85
4	RG08	0B6573	RM	M04	0.85
5	RG06	0B4240	Junior associate RM	N05	0.85
No.	Region	Branch	Position	Name	Score
1	RG07	0B6780	RM senior	O01	0.45
2	RG04	0B5635	RM consumer	G02	0.45
3	RG04	0B5738	RM	A03	0.45
4	RG25	0B6204	Junior associate RM	R04	0.46
5	RG12	0B5041	RM	I05	0.46

Note: Regional (RG).

The findings provided valuable insights into the significant impact of various indicators on the elements of the fraud triangle (pressure, opportunity and rationalization) in the context of microloan services. All 23 indicators examined were significant underscoring their importance in identifying potential fraud risks associated with the microloan RM. The Confirmatory Factor Analysis (CFA) further corroborates these findings establishing that pressure exerts the most substantial influence on the probability of fraud within microloan services. Specific parameters such as 'working unit' and outstanding loans are significant contributors to the predictive power of the fraud risk model. This result highlights the critical need to address these identified indicators and factors to effectively mitigate fraud risks in microloan services and enhance overall risk management strategies within financial institutions.

Moreover, microfinance institutions play a vital role in reducing fraud as exemplified by research on efforts undertaken by various microfinance institutions including the Bank Rakyat Indonesia (BRI) Unit. The latter has implemented rigorous internal monitoring, comprehensive auditing practices and robust financial processes that significantly contribute to effective fraud prevention within the organization. Good financial risk management is considered a crucial component for the success of microfinance institutions ensuring robust risk mitigation strategies that safeguard the institution and its clients. This aligns with research conducted by Anastasya and Noviyanti [35] that examined the application of the GRC in rural banks (Bank Perkreditan Rakyat/BPR), a financial services company that serves microloans. The result showed that of the GRC concept used i.e., governance risk, and compliance only risk variable significantly influences company performance both financial and non-financial performance. According to the GRC Maturity Survey 2019 by the Open Compliance and Ethics Group (OCEG), only 14% of respondents had completely or significantly integrated GRC processes and technology. Meanwhile, 23% of respondents still have siloed (not integrated) GRC whereas the rest do not have acceptable GRC maturity levels.

5. Conclusion

This research demonstrates the value of data analytics in predicting fraud risks inherent in microloan services and supporting financial institutions in devising preventive strategies. The fraud triangle model identifies employee pressure as the most influential driver of fraud probability indicating that mitigation efforts should address contributory pressures. Practices that heighten demands on relationship managers can be strategically alleviated to reduce misconduct. However, a nuanced approach is necessary to balance business objectives, risk levels and employee welfare. Measures to minimize pressure such as performance benchmarks or incentive structures must align with responsible growth and sustainability models. As microloans expand financial access, balancing prudence and social impact is vital.

The study also underscores the importance of integrated GRC in navigating microloan intricacies. Financial institutions must maintain diligent governance, vigilant risk monitoring, robust control systems and regular audits to combat fraud. The predictive model provides a robust diagnostic tool to identify suspicious behaviours based on risk scores for timely intervention. This enables cost savings and the safeguarding of assets and reputation. Further analysis can refine the model to balance false positives and negatives for optimal accuracy. Additional qualitative and quantitative evaluation across diverse banks and non-bank institutions can offer more representative insights. Broadening the research scope could aid in developing anti-fraud frameworks tailored to the specificities of varied financial contexts across Indonesia.

Nonetheless, this study sets a valuable precedent for harnessing data analytics to uphold the integrity, efficiency and stability of micro financial services through integrated GRC. The approach and findings can inform fraud mitigation best practices for policymakers and practitioners identical. However, sustained outcomes require regular reviews of risk protocols, widening data sources for the predictive model, monitoring effectiveness and recalibrating mechanisms accordingly. A comprehensive policy also entails strengthening legal frameworks and whistleblower protections. Ultimately, this research highlights the need for a principled stance. Fraud in microloans betrays their socially empowering promise. Integrated mechanisms centred on ethics and accountability should undergird microfinancing growth. In a broader context, balanced regulate-innovation pathways can nurture entrepreneurship and financial access while safeguarding the Indonesian economy's stability. This research demonstrates the immense value of predictive analytics in estimating fraud risks to enable precisely targeted, proactive prevention strategies for financial institutions. Pressure mitigation through optimally balanced performance benchmarking systems and responsible and sustainable growth models is critical to reducing the propensity for misconduct among employees. Computationally deriving individualized risk profiles allows for corrective interventions that strategically alleviate work-related demands before they become criminogenic. Similarly, integrated governance, risk and compliance (GRC) controls undergirded by managerial diligence and systemic vigilance provide a robust bulwark against fraud. The predictive model constructed here offers a precise diagnostic to accurately rank individuals by risk scores facilitating prompt interception of suspicious activity patterns. Thereby, predictive capabilities uphold functional integrity in widely dispersed microloan services informing policy and practice for optimal outcomes. However, sustained success requires building upon these foundations through regular reviews, progressively widening data collection scopes, monitoring system effectiveness and prompt recalibrations whenever needed.

5.1. Implications

In terms of policy implications, this approach highlights the need for comprehensive frameworks that complement digitized diagnostics with holistic protections centred on accountability and transparency. Beyond technical fixes, contradicting the socially detrimental effects of fraud requires principled leadership and strengthened legal scaffolds, including robust whistle-blower safeguards. Ultimately, this research focuses on the necessity of a proactive ethical stance towards microfinancing allowing misconduct to permeate these services through any means betrays their socially empowering promise of equitable access for vulnerable communities. In terms of practical implications, the study offers a template for stakeholders to uphold integrity as an organizational cornerstone while harnessing computational innovations. The integrated infrastructure blending contextualized data analytics with customized GRC protocols promises sustainable pathways to balance innovation incentives with risk management imperatives. Thus, the approach here strives to provide all employees, leaders and technologists with actionable next steps to synergize growth and trust.

5.2. Limitations

However, the research has limitations worth acknowledging when interpreting the abovementioned implications. Firstly, given the sole reliance on past employee data from a few Indonesian banks, the sample has constraints around broader representativeness. While still yielding useful indicators, expanding the analytical purview across diverse financial institutions can paint a more granular picture of tailored anti-fraud frameworks specific to varied institutional contexts. Additionally, the predictive model exhibits inherent trade-offs around balancing false positives versus false negatives that warrant continual refinement through further qualitative and quantitative assessments. A comparative investigation of computational techniques and indicator optimizations tailored to different microfinancing ecosystems can aid these efforts to improve model performance holistically based on updated environmental insights.

5.3. Future Research

Future research avenues exist for evaluating the transferability and generalizability of these predictive capabilities given broader globalized sets of contextual parameters beyond Indonesia. As financial technologies proliferate across borders, cross-country collaboration is critical to deriving internationally applicable models with customizable components to maintain local relevance. Beyond banking, the techniques can be tested for mitigating misconduct in broader funding ecosystems spanning digital microcredit, crowdfunding platforms and peer-to-peer lending facilitated through mobile applications. Additionally, exploratory field studies grounded in sociological theory around behavioural norms and fraud rooted in social relationships versus digital-only transactions can uncover supplementary socio-technical dynamics to incorporate into next-generation hybrid models. Advancing the interdisciplinary analytical lens by bridging computational techniques with ethical and social insights holds much promise for financial inclusion efforts worldwide.

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