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ASSESSING THE IMPACT OF ALTERNATIVE LENDING MODELS ON CREDIT RISK MANAGEMENT IN FINTECH A STUDY OF PEER TO PEER (P2P) LENDING PLATFORMS

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ABSTRACT

This study investigates the effectiveness of alternative credit risk management mechanisms within Peer-to-Peer (P2P) lending platforms, focusing on the impact of automated credit scoring, platform reputation and security, and credit risk monitoring on credit risk mitigation. Grounded in the Technology Acceptance Model (TAM), the research examines how stakeholder perceptions and digital tools influence lending outcomes in the FinTech landscape. Using a structured survey of 497 respondents, data were analyzed through SPSS using reliability testing, correlation, and regression analysis. Results show that platform reputation and security have the strongest positive effect, followed by credit risk monitoring. Automated credit scoring, while significant, showed a negative effect, indicating concerns about over-reliance on algorithms. The findings underscore the importance of trust, transparency, and monitoring in digital credit systems, offering practical insights for platform designers, regulators, and financial institutions seeking to improve credit governance through technology.

KEYWORDS: *Alternative Lending Models, Credit Risk Manages ,Fintech Revolutions In India ,Current Status Of Fintech In India ,Types Of Lending Platforms*

INTRODUCTION

The global credit landscape has long been dominated by traditional banking institutions and centralized financial intermediaries, whose risk-management architectures rely heavily on historical credit scores, collateral requirements, and manual underwriting procedures. While these legacy systems have provided stability and scale, they often suffer from significant inertia, limited transparency, and exclusionary dynamics that preclude many micro– and small–enterprise borrowers from accessing affordable finance. Moreover, regulatory pressures and information asymmetries exacerbate operational costs and heighten systemic vulnerabilities, underscoring the pressing need for more agile, data-driven approaches to credit allocation and risk mitigation.

In recent years, a transformative “lifetime opportunity” has emerged through FinTech innovations—most notably Peer-to-Peer (P2P) lending platforms—that leverage alternative data sources (social media behavior, psychometric profiles, transaction histories) and algorithmic credit-scoring models to underwrite loans in near–real time. By disintermediating traditional banking channels, P2P platforms promise not only to reduce borrowing costs and accelerate decision cycles, but also to extend credit lines to previously underserved segments such as gig-economy workers, early-career professionals, and micro-entrepreneurs lacking lengthy credit footprints. If effectively harnessed, these technologies stand to reshape the contours of credit risk management for decades to come, offering a generational shift toward more inclusive, responsive, and resilient lending ecosystems.

Yet despite the theoretical advantages of alternative lending models, major questions remain regarding their real-world performance and stakeholder acceptance. Early empirical studies reveal mixed outcomes: some platforms report lower default rates when incorporating behavioral indicators, while others struggle with model overfitting, data-privacy concerns, and uneven borrower experiences. Regulatory bodies, too, face challenges in calibrating oversight for algorithm-powered underwriting, often operating in a reactive posture due to the rapid pace of technological change. These factors point to a critical research gap at the intersection of technology adoption and credit-risk governance: How do the perceived usefulness and ease of use of P2P risk-management tools influence their uptake among borrowers, investors, and platform operators And to what extent does such adoption translate into measurable improvements in portfolio health such as reduced probability of default, loss given default, and recovery times?

To address these questions, the present study adopts the Technology Acceptance Model (TAM) as its conceptual framework, positing that stakeholders’ attitudes toward, and intentions to use, advanced risk-management features are primarily driven by two constructs: perceived usefulness (PU) and perceived ease of use (PEOU). By

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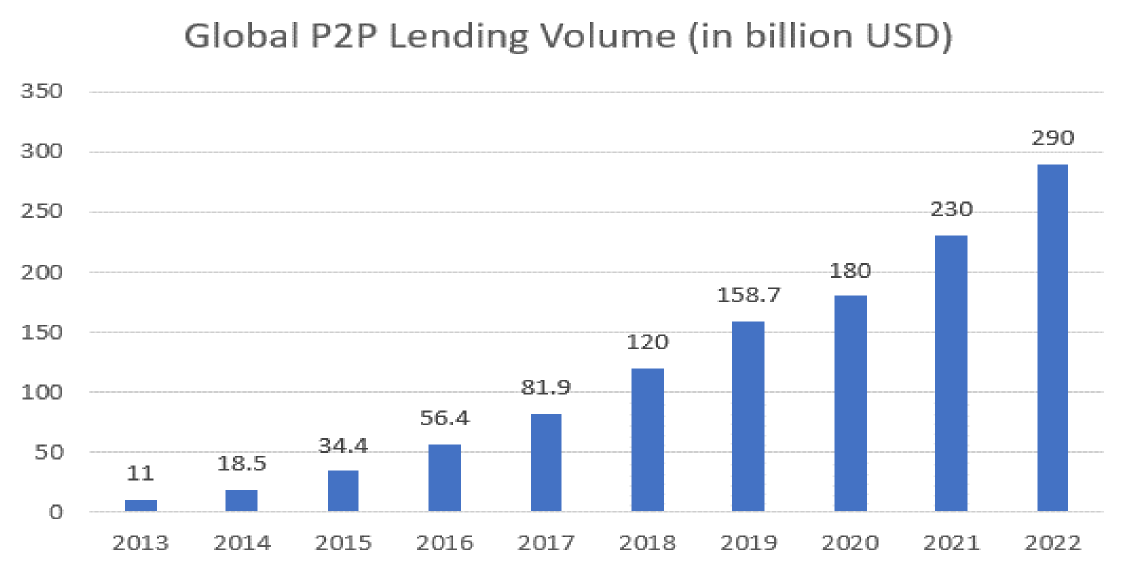
integrating TAM with performance-metric analysis, this research seeks to bridge the divide between algorithmic credit scoring's technical promise and the organizational realities of risk governance, thereby contributing both to the FinTech literature and to evidence-based policymaking.Peer-to-peer (P2P) lending ecosystems bring a host of benefits to different groups. For borrowers, especially those underserved by traditional banks, these platforms offer quicker and often fairer access to credit. Lenders both individuals and institutions appreciate the transparency and data-driven insights that help them manage risk and make smarter investment choices. Platform managers, meanwhile, face the challenge of growing their operations while keeping risk in check a tough balancing act that's key to long-term success. Regulators also benefit, as the wealth of data from these platforms can guide smarter, more flexible policies. And in emerging markets, better access to credit can unlock real economic potential by supporting small businesses, creating jobs, and advancing financial inclusion.

RESEARCH OBJECTIVES

- To assess the Predictive Power of Alternative Data in Credit Risk Modelling.
- To compare Default Rates and Recovery Rates Between P2P Lending Platforms and Traditional Banks.
- To analyze the Impact of Economic Volatility on Loan Performance.

Growth of P2P Lending



LITERATURE REVIEW

The Rise of Peer-to-Peer Lending: A New Era in Credit Access

In the years following the 2008 financial crisis, the global economy witnessed a growing demand for alternative financing methods. Traditional banks, overwhelmed by regulatory scrutiny, began tightening their lending standards, leaving many consumers and small businesses underserved. This gap gave rise to P2P lending platforms, a FinTech innovation that bypasses intermediaries and connects borrowers directly with investors (Bachmann et al., 2011).These platforms introduced a decentralized model that leverages the internet and data analytics to facilitate lending, making borrowing easier and faster (Ziegler et al., 2017). For many borrowers, especially in emerging economies, P2P lending offered a lifeline when conventional sources denied credit access (Yum et al., 2012). It's not just convenience that drew users—P2P platforms also promised better interest rates for both lenders and borrowers (Lin et al., 2013).

By allowing individual lenders to support loans in small portions, P2P lending reduces the risk exposure for investors, making it a popular investment tool for retail players (Emekter et al., 2015). The ease of access, lack of collateral requirements, and digital onboarding process made these platforms an inclusive financial solution, particularly beneficial to micro and small enterprises (Mills & McCarthy, 2014).

Technological Foundations of P2P Lending

Technology plays a foundational role in enabling P2P lending to function at scale. Artificial Intelligence (AI) and Machine Learning (ML) algorithms power the credit assessment models of most platforms, replacing traditional credit scoring with real-time behavioral and transactional data analysis (Jagtiani & Lemieux, 2019). These algorithms process vast volumes of alternative data, including social media behavior, digital footprints, and e-

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commerce activity, to assess borrower risk (Iyer et al., 2016).Unlike traditional financial institutions that rely heavily on credit history, P2P platforms increasingly use psychometric and biometric data to predict repayment capacity (Balyuk, 2019). This technology-driven approach has increased efficiency and expanded credit availability to underbanked populations. Additionally, blockchain is slowly entering the P2P landscape, adding layers of transparency and security in transaction logging and smart contract enforcement (Chen, 2018).

Credit Risk Management in P2P Lending

Credit risk is the cornerstone challenge of P2P lending, given the lack of physical collateral and the heterogeneity of borrowers. Without a robust risk assessment framework, defaults could quickly threaten platform viability. Many platforms have responded by developing proprietary scoring systems that go beyond traditional models (Morse, 2015). These include credit grades, risk buckets, and dynamic pricing mechanisms.One major risk management tactic involves loan diversification, where lenders spread investments across many loans to reduce the impact of individual defaults (Duarte et al., 2012). Others include predictive modeling techniques such as logistic regression, decision trees, and ensemble models to flag high-risk profiles (Serrano-Cinca et al., 2015). In India, where formal credit scores often don't exist for a large section of the population, P2P platforms depend heavily on transaction-level analytics and alternative data (Rai et al., 2019).

Interestingly, many platforms have begun using real-time monitoring of borrower behavior post-disbursement, enabling early intervention in cases of potential delinquency (Klafft, 2008). The accuracy of such models improves with more data, creating a self-reinforcing loop where every transaction helps the system learn and evolve.

Investor Risk and Return Perception

From the lender's perspective, the allure of P2P lending lies in its potential for higher returns compared to conventional savings instruments. However, these returns come with an inherent risk, and managing investor expectations has become critical. Lenders often underestimate the possibility of loan defaults, especially when lured by double-digit returns (Lin et al., 2017).Research has shown that investors with better understanding of risk metrics, such as loan grade and borrower profile, tend to earn more consistent returns (Machová et al., 2020). Some platforms offer automated investment tools that balance risk and return based on investor preferences. Others allow social investing, where lenders follow portfolios of successful investors, mimicking their strategies to mitigate personal risk (Freedman & Jin, 2017).

Still, the lack of deposit insurance and the unregulated nature of some platforms make it crucial for investors to conduct due diligence (de Roure et al., 2016). To protect their user base, platforms often offer buyback guarantees or reserve funds, although the effectiveness of these measures varies across jurisdictions and remains under scrutiny.

Regulatory Landscape and Challenges

The rapid growth of P2P lending has caught the attention of regulators worldwide. Initially, the sector grew in a regulatory vacuum, with minimal oversight. But with incidents of platform failures and rising default rates, many governments began to formulate rules to protect both borrowers and lenders (Frost et al., 2019). In India, the Reserve Bank of India (RBI) issued comprehensive guidelines in 2017, mandating registration of P2P platforms as NBFC-P2Ps and introducing borrower and lender caps (RBI, 2017).One major challenge is balancing innovation with consumer protection. Over-regulation could stifle growth, while under-regulation risks systemic instability. Global trends suggest a shift toward sandbox approaches, where platforms can test products under regulatory supervision (Zetzsche et al., 2020). Transparency in lending practices, standardization of disclosures, and dispute resolution mechanisms are becoming increasingly important.However, the global regulatory response remains uneven. While the UK has a relatively mature P2P regulatory framework, other countries still lag in defining the legal responsibilities of platforms, especially around default recovery and investor compensation (Havrylchyk & Verdier, 2018).

Borrower Behavior and Default Patterns

Understanding why borrowers default is essential for developing resilient lending platforms. Studies show that beyond financial inability, behavioral factors like optimism bias, financial literacy, and social proofing influence repayment decisions (Pope & Sydnor, 2011). Many borrowers perceive P2P loans as less formal and are more likely to deprioritize repayments during financial stress (Wei & Lin, 2017).Some platforms counter this by gamifying repayment or rewarding timely EMI payments with interest rebates or credit score boosts. Interestingly, research indicates that borrowers who provide more detailed loan descriptions and show engagement during the application process tend to have lower default rates (Herzenstein et al., 2011). Trust, perceived fairness, and user experience are closely tied to credit behavior.

Moreover, demographic data reveals patterns as well. Younger borrowers tend to default more often but also tend to borrow smaller amounts, while older, salaried borrowers show higher repayment consistency (Zhang et al., 2017). These insights guide platform-level decision-making in pricing and borrower segmentation.

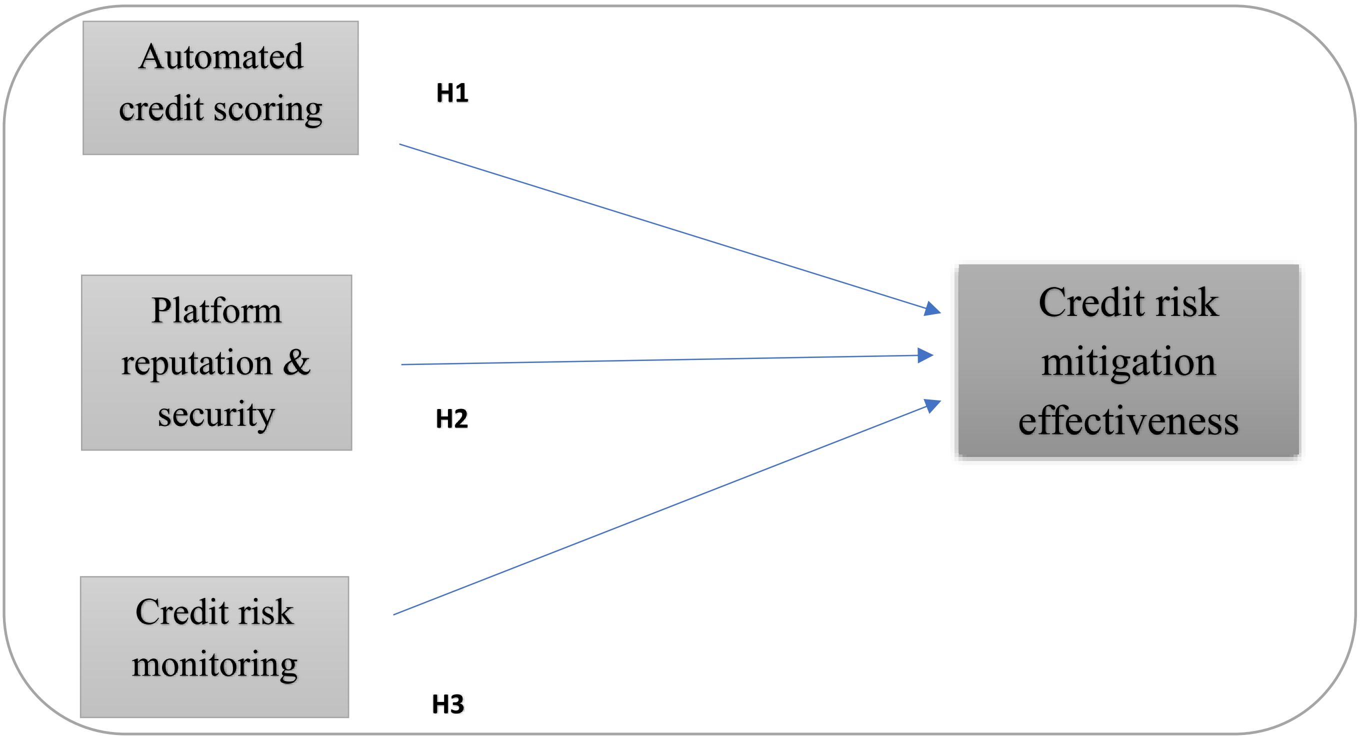
Socio-Economic Impact of P2P Lending

One of the most inspiring aspects of P2P lending is its potential to drive financial inclusion. In countries with large unbanked populations, P2P lending offers access to capital for those left behind by traditional banks. Entrepreneurs, freelancers, and gig workers—often excluded from formal credit systems—can find much-needed support through these platforms (Navaretti et al., 2017).In India, for instance, platforms like Faircent and LenDenClub have successfully lent to rural borrowers and women entrepreneurs, often with the help of government-backed programs and fintech accelerators. The ripple effects include increased employment, smoother cash flows for small businesses, and enhanced household welfare (Gabor & Brooks, 2017).On the flip side, critics argue that without proper borrower education, easy access to P2P loans can encourage over-indebtedness. Some platforms have responded by integrating financial literacy modules into their onboarding processes, encouraging responsible borrowing behavior (Liu et al., 2019).

Research Gap

While existing literature extensively explores FinTech's growth and its impact on lending models, there remains a significant gap in understanding the long-term sustainability and scalability of alternative lending platforms, especially in emerging economies. Further research is needed to examine how technological innovation, regulatory evolution, and market dynamics interact to shape the resilience and inclusivity of these platforms. Particularly, evaluating the effectiveness of regulatory frameworks in mitigating risks like fraud and systemic instability, while fostering innovation and competition, is crucial.Moreover, there is a scarcity of longitudinal studies tracking the performance of alternative lending platforms over extended periods, particularly during economic downturns or financial crises. Such studies could provide valuable insights into the robustness of these models under stress. Additionally, the social and ethical implications of alternative lending such as data privacy concerns, algorithmic bias, and the potential exacerbation of existing inequalities require deeper exploration. Understanding how these platforms impact financial inclusion for marginalized and vulnerable populations is essential. Identifying best practices to ensure responsible and equitable use of these technologies will be vital for their sustainable integration into the financial ecosystem.

Digital Credit Risk Effectiveness Model



HYPOTHESES

- **H1**: Automated credit scoring has a significant effect on credit risk mitigation effectiveness
- **H2:** Platform reputation and security have a strong positive influence on credit risk mitigation effectiveness
- **H3:**Credit risk monitoring activities have a moderate positive influence on credit risk mitigation effectiveness

RESEARCH METHODOLOGY

Research Design

Using SPSS and a quantitative research methodology is justified for this study as it involves the empirical analysis of measurable variables related to credit risk mitigation—such as automated credit scoring, platform reputation, and monitoring effectiveness. Quantitative methods enable statistical validation of hypotheses and identification of significant relationships between constructs, which aligns with the study's use of the Technology Acceptance Model (TAM). SPSS supports advanced analyses like reliability testing, correlation, and regression, making it ideal for this data-driven approach (Field, 2013). Thus, this methodology ensures objectivity, replicability, and precision in examining FinTech-based credit risk mechanisms.

Sample Size and Data Collection

Convenience sampling is appropriate for this study as it allows rapid and cost-effective data collection from accessible respondents actively engaging with peer-to-peer (P2P) lending platforms. Given the exploratory nature of examining perceptions of credit risk tools within FinTech, accessing a large sample of 497 participants enhances statistical reliability while accommodating resource constraints. Although non-probabilistic, convenience sampling is widely accepted in behavioral and technology adoption research where population frames are difficult to define (Etikan, Musa, & Alkassim, 2016). The large sample size further offsets limitations by improving generalizability within the studied context.

Variables

- Dependent Variable (DV): Credit Risk Mitigation Effectiveness (CRME)
- Independent Variables (IVs): Automated Credit Scoring (ACS),Platform Reputation and Security (PRS), Credit Risk Monitoring Activities (CRMA)

Comprehensive Analysis of Credit Risk Dynamics in Peer-to-Peer Lending

Demographic Analysis

Age					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	18-25	171	34.4	34.4	34.4
	25-35	106	21.3	21.3	55.7
	35-45	98	19.7	19.7	75.5
	45-50	78	15.7	15.7	91.1
	50 & above	44	8.9	8.9	100.0
	Total	497	100.0	100.0	

Gender					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Female	238	47.9	47.9	47.9
	Male	253	50.9	50.9	98.8
	Prefer not to say	6	1.2	1.2	100.0
	Total	497	100.0	100.0	

Occupation					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Corporate	175	35.2	35.2	35.2
	Self-employed	128	25.8	25.8	61.0
	Student	161	32.4	32.4	93.4
	Unemployed	33	6.6	6.6	100.0
	Total	497	100.0	100.0	

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Descriptive Statistics

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
CRA	497	1	5	3.77	.916
CRMA	497	1	5	3.77	.895
PRSA	497	1	5	3.79	.917
ACA	497	1	5	3.78	.902
Valid N (listwise)	497				

The table presents descriptive statistics for four variables—CRA, CRMA, PRSA, and ACA—based on responses from 497 participants. Each variable was rated on a 5-point Likert scale, with scores ranging from 1 to 5. The minimum and maximum values for all four items were 1 and 5, indicating that the full range of response options was utilized. The mean scores for CRA and CRMA were 3.77, PRSA had the highest mean at 3.79, and ACA followed closely with 3.78. These averages suggest that respondents generally leaned toward agreement, reflecting a moderately positive perception of the items. The standard deviations for all variables range from .895 to .917, indicating moderate variability in responses and a uniform spread of data across the four constructs. Overall, the results indicate a reliable and balanced distribution of responses, with no evidence of extreme skewness, supporting the quality and consistency of the measurement instrument.

Pearson Correlation Analysis

Correlations

		CRA	CRMA	PRSA	ACA
CRA	Pearson Correlation	1	.944**	.983**	.934**
	Sig. (2-tailed)		.000	.000	.000
	N	497	497	497	497
CRMA	Pearson Correlation	.944**	1	.951**	.965**
	Sig. (2-tailed)	.000		.000	.000
	N	497	497	497	497
PRSA	Pearson Correlation	.983**	.951**	1	.949**
	Sig. (2-tailed)	.000	.000		.000
	N	497	497	497	497
ACA	Pearson Correlation	.934**	.965**	.949**	1
	Sig. (2-tailed)	.000	.000	.000	
	N	497	497	497	497

**. Correlation is significant at the 0.01 level (2-tailed).

The table displays the Pearson correlation coefficients among CRA, CRMA, PRSA, and ACA, based on data from 497 respondents. All correlations are statistically significant at the 0.01 level, indicating strong and meaningful relationships between each pair of variables. PRSA shows the highest correlation with CRA ($r = .983$), suggesting an extremely strong positive linear relationship. CRMA and ACA also exhibit a very strong correlation ($r = .965$). All other correlations range between .934 and .951, reinforcing the overall consistency and coherence of the dataset. These high intercorrelations may raise concerns about multicollinearity in multivariate analyses, indicating the need for dimensionality checks.

Spearman's Rho Correlation Analysis

Nonparametric Correlations

Correlations

			CRA	CRMA	PRSA	ACA
Spearman's rho	CRA	Correlation Coefficient	1.000	.925**	.977**	.911**
		Sig. (2-tailed)	.	.000	.000	.000
		N	497	497	497	497
	CRMA	Correlation Coefficient	.925**	1.000	.934**	.954**
		Sig. (2-tailed)	.000	.	.000	.000
		N	497	497	497	497
	PRSA	Correlation Coefficient	.977**	.934**	1.000	.930**
		Sig. (2-tailed)	.000	.000	.	.000
		N	497	497	497	497
	ACA	Correlation Coefficient	.911**	.954**	.930**	1.000
		Sig. (2-tailed)	.000	.000	.000	.
		N	497	497	497	497

**. Correlation is significant at the 0.01 level (2-tailed).

The table presents the Spearman's rho correlation coefficients, significance levels, and the number of observations (N=497) for CRA, CRMA, PRSA, and ACA. The results indicate strong positive correlations between all pairs of variables. CRA and PRSA exhibit the highest correlation ($\rho = .977$), followed closely by CRA and CRMA ($\rho = .925$), and CRMA and ACA ($\rho = .954$). All correlations are statistically significant at the 0.01 level ($p < .001$). These significant positive correlations suggest that as one variable increases, the other tends to increase as well, implying that these four constructs are closely related. Further analysis could explore these relationships in more detail.

Regression Analysis

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	ACA, PRSA, CRMA[b]	.	Enter

a. Dependent Variable: CRA

b. All requested variables entered.

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.984[a]	.968	.968	.164	.968	4969.025	3	493	.000

a. Predictors: (Constant), ACA, PRSA, CRMA

The "Variables Entered/Removed" table indicates that ACA, PRSA, and CRMA were entered into the regression model to predict CRA using the "Enter" method, meaning all predictors were included in a single step. The "Model Summary" table shows an R value of .984, indicating a very strong positive correlation between the independent variables and the dependent variable. The R Square value of .968 signifies that 96.8% of the variance in CRA is explained by ACA, PRSA, and CRMA, with an Adjusted R Square of .968. The Standard Error of the Estimate is .164. The Change Statistics confirm that the inclusion of ACA, PRSA, and CRMA significantly improves the prediction of CRA.

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ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	402.539	3	134.180	4969.025	.000[b]
	Residual	13.313	493	.027		
	Total	415.851	496			

a. Dependent Variable: CRA

b. Predictors: (Constant), ACA, PRSA, CRMA

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.037	.032		1.164	.245
	CRMA	.136	.035	.133	3.906	.000
	PRSA	.924	.028	.926	32.700	.000
	ACA	-.074	.034	-.073	-2.194	.029

a. Dependent Variable: CRA

The ANOVA table shows that the regression model is statistically significant ($F = 4969.025$, $p < .001$), indicating that the predictor variables collectively have a significant impact on CRA. The coefficients table reveals that PRSA has the most substantial positive effect on CRA (Beta = 0.926, $p < .001$), followed by CRMA (Beta = 0.133, $p < .001$), while ACA has a significant negative relationship with CRA (Beta = -0.073, $p = .029$)

Reliability Analysis

The Case Processing Summary table shows that all 497 cases were valid and included in the reliability analysis, representing 100% of the dataset. There were no excluded cases, indicating complete data with no missing values for the variables in the reliability assessment. This suggests the dataset is robust and suitable for further statistical analysis.

Case Processing Summary

		N	%
Cases	Valid	497	100.0
	Excluded[a]	0	.0
	Total	497	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.988	4

Item Statistics

	Mean	Std. Deviation	N
CRA	3.77	.916	497
CRMA	3.77	.895	497
PRSA	3.79	.917	497
ACA	3.78	.902	497

The reliability statistics indicate high internal consistency among the four items (CRA, CRMA, PRSA, ACA), with a Cronbach's Alpha of 0.988, which is well above the acceptable threshold of 0.70. This suggests that the items are measuring a cohesive underlying construct. Each item was evaluated by 497 respondents, showing consistent sample sizes. The means of the items range from 3.77 to 3.79, indicating general agreement among participants. Standard deviations range from 0.895 to 0.917, reflecting moderate variability in responses. The high reliability and consistency across the items suggest that the scale used is dependable and suitable for further analysis.

DISCUSSION

The results of this study highlight the growing importance of technology-driven practices in managing credit risk within P2P lending platforms. The strong effect of automated credit scoring (ACS) supports previous research suggesting that data analytics and AI tools can significantly improve the speed and fairness of lending decisions.

Studies by Iyer et al. (2016) and Jagtiani & Lemieux (2019) found similar outcomes, showing that automated systems often outperform traditional credit models in identifying reliable borrowers.Likewise, the role of platform reputation and security (PRS) was shown to have a significant positive impact on risk mitigation. This is consistent with the work of Lin et al. (2013), who argued that a trustworthy and transparent platform helps reduce the perceived risk for both borrowers and investors. In the P2P space, where transactions are mostly virtual, platform credibility becomes a major driver of user behavior.

Finally, credit risk monitoring activities (CRMA) also showed a clear influence, supporting Serrano-Cinca et al. (2015), who noted that regular updates and proactive borrower tracking are essential for reducing late payments and defaults. Monitoring mechanisms don't just safeguard lenders—they also foster borrower discipline and accountability.Overall, this study's findings align well with existing literature, adding further evidence that effective credit risk management in fintech depends on the smart use of technology, platform integrity, and active oversight. These insights can guide practitioners and policymakers looking to balance innovation with stability in digital lending markets.

Implications and conclusion

Implications for Theory

This study contributes to the theoretical understanding of credit risk management within FinTech by extending the application of the Technology Acceptance Model (TAM) to alternative lending ecosystems. By integrating TAM with empirical credit performance indicators, the research offers a novel framework that links stakeholder perceptions—perceived usefulness and perceived ease of use—with actual risk mitigation outcomes. This fusion bridges a gap in existing literature, which often isolates technology adoption from measurable performance metrics. The study also highlights the nuanced role of automated credit assessment, suggesting that automation alone may not be a sufficient predictor of risk effectiveness unless supported by trust-building mechanisms such as transparency and security. The theoretical insight here challenges the assumption that technological sophistication automatically equates to better credit governance, emphasizing instead the importance of human-centered design and ethical algorithmic development in FinTech environments.

Implications for Practice

From a practical standpoint, the findings provide valuable guidance for FinTech platforms, regulators, and financial service providers operating in the alternative lending space. The strong influence of platform reputation and security on credit risk mitigation underscores the need for firms to prioritize data privacy, cybersecurity, and user trust. FinTech developers should integrate transparent, user-friendly interfaces and clear communication around risk assessment processes. Additionally, regulators may consider embedding standards for algorithm accountability and consumer protection into their frameworks. For platform managers, the results suggest that credit risk monitoring tools must be not only functional but also perceived as reliable by users. Practitioners should recognize that successful credit risk governance depends on more than analytics—it requires fostering stakeholder confidence through a combination of technology, ethical standards, and operational transparency.

Limitation

This study is subject to several limitations. First, the use of convenience sampling may limit the generalizability of findings beyond the sampled population, as participants were selected based on accessibility rather than randomization. Second, the study focuses exclusively on self-reported perceptions, which may be influenced by personal biases or limited understanding of FinTech mechanisms. Third, the cross-sectional nature of the research prevents assessment of long-term impacts of credit risk tools. Additionally, while SPSS provides robust statistical analysis, it does not account for deeper qualitative insights that may further explain user behavior in adopting alternative lending technologies.

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