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Impact of Artificial Intelligence on Credit Assessment in Microfinance Banks in Nigeria

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ABSTRACT

The rapid expansion of Nigeria's digital lending industry has led to the development of effective credit risk assessment systems. The low credit histories and strong information asymmetry were two of the numerous issues that the traditional credit scoring algorithms had to deal with. The impact of artificial intelligence (AI) on credit evaluation in Nigerian microfinance institutions is investigated in this study. 125 credit officers, compliance managers, and IT specialists from microfinance institutions provided the information. The measurement and structural models are analyzed using Partial Lease-Structural Equation Modeling (PLS-SEM). In order to fully achieve the potential of AI-enabled credit management, the study suggests investments in employee training, explainable AI models, and regulatory norms. The results show that AI has a major impact on loan payment and credit evaluation in Nigerian microfinance banks.

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1. INTRODUCTION

Artificial intelligence (Al) is now actively involved in changing credit and debt management in financial systems, directly affecting who can obtain loans, how quickly decisions are made, and how repayment risks are tracked (Reuters, 2025; Faheem, 2021). Al is no longer merely a lab curiosity. Strong support for Al in emerging economies is accompanied by growing concerns about trust, justice, and governance, according to regional and global surveys. This combination is especially important for financial services in nations like Nigeria, where a sizable informal sector and a lack of historical credit data present both opportunity and risk (Reuters, 2025; Forbes Africa, 2025). At the policy level, Nigerian authorities have highlighted digitization while cautioning about operational and data-governance risks- signals that make the societal reception of AI in credit markets a managerial and regulatory concern (Bello, 2022; Central Bank of Nigeria, 2023).

Although conventional approaches are still utilized and give decent results, there is a rising tendency towards modern credit risk assessment instruments in nations such as Nigeria (Aladejubelo, 2026). Individuals with short credit histories are increasingly able to acquire credit with current credit evaluation (Brown, 2024). Historically, Nigerian banks, microfinance in particular have relied on bureau scores, collateral requirements, and credit officers' judgment procedures that work poorly where official credit histories are sparse and where speed and size matter (Central Bank of Nigeria, 2023; Akinyemi, 2023). However, in Nigerian samples and similar contexts, machine-learning techniques and alternative data approaches have shown improved predictive performance, resulting in higher hit rates in default classification and enabling near-real-time scoring that, when used responsibly, can expand credit access (Akinyemi, 2023; Ayobami, 2023; Faheem, 2021). However, operational capability, explainability, and stakeholder trust mediate whether algorithmic improvements result in improved repayment outcomes and sustainable financial inclusion; technological accuracy is only one component of the adoption puzzle (Faheem, 2021; Ogirala et al, 2025).

This study fills a critical void. The literature that is currently available is divided into two strands: one assesses the predictive performance of algorithms, while the other addresses ethics, explainability, and regulation. Only a small number of studies empirically connect these strands by looking at the perceptions of bankers, compliance officers, and borrowers and determining whether those perceptions influence behavior like override decisions, monitoring intensity, or borrower responses to automated decisions (Ogirala et al, 2025; Faheem, 2021; Ogala, 2025). In the absence of this bridge, banks run the risk of implementing technically better models that are institutionally or socially misaligned, leading to disputed denials, officer overrides that disprove algorithmic signals, or customer disengagement that increases non-performing loans (Forbes Africa, 2025; Global Legal Insights, 2025).

The urgency is reinforced by tangible local signs. Perception-driven friction can have actual reputational, compliance-related, and financial costs due to the Central Bank's digitalization agenda, recent regulatory updates impacting fintech and data practices, and observed operational constraints in credit monitoring (Central Bank of Nigeria, 2023; Bello, 2022; Global Legal Insights, 2025). A perception-focused study is directly relevant to practitioners and policymakers because empirical case studies and theses in the Nigerian context demonstrate promising algorithmic accuracy in microfinance and bank datasets, but they also report uneven institutional readiness and variable public trust (Akinyemi, 2023; Ayobami, 2023; Ogala, 2025). The technical and the social are thus linked in this perception study. It looks on the perceptions of credit officers, compliance/regulatory personnel, and retail borrowers regarding Al and its possible impact on loan repayment dynamics and credit assessment systems.

There are advantages and disadvantages to the banking industry's use of artificial intelligence (AI) in credit risk assessment procedures. Although AI-powered algorithms have demonstrated promise in improving predictive analytics and automating decision-making procedures, issues with their dependability, transparency, and potential biases still exist. Investigating how much these technologies help to more accurate risk assessments and whether they add new sources of uncertainty or systemic concerns is crucial as AI algorithms increasingly dominate credit risk assessment (Mironiuc, 2021). In addition, the quick development of AI technologies and their use in credit risk assessment poses ethical and regulatory concerns, especially with regard to algorithmic transparency, data privacy, and fair lending practices (Mugume & Taremwa, 2021). In order to handle these new issues and guarantee the honesty and equity of lending procedures, a thorough analysis of the impact of AI on credit risk assessment in Nigerian microfinance institutions is crucial.

2. LITERATURE REVIEW

2.1 Artificial intelligence

Artificial intellect (AI) is the display of intellect by robots that have the fundamental traits of human intelligence. Because of its capacity to replicate human problem-solving skills, the original AI was dubbed the first General Problem Solver (GPS) (Babarinde et al., 2025). It can be defined as a general mental aptitude for knowledge acquisition, logical reasoning, and problem solving (Goyal et al., 2025). Additionally, it uses complex algorithms and mathematical computers to track customer and employee behavior using unsupervised learning systems (Nambie et al., 2024). Generally speaking, the financial services industry and the global economy stand to gain significantly from AI. With investments of over 11 billion US dollars in 2020, the financial sector has made a significant contribution to AI (Goyal et al., 2025). According to a recent study (Brown, 2024), AI can benefit the global banking industry by up to USD 1 trillion every year. The main cause of this is the widespread application of AI in the reorganization of financial operations.

2.2 Artificial Intelligence and Credit Assessment

Prior empirical research has examined how artificial intelligence improves loan repayment and credit evaluation in the Nigerian banking sector, concentrating on machine learning algorithms and alternate data sources to increase inclusion and accuracy.

Aladejubelo (2026) uses simulated panel data depicting fintech lending activities between 2017 and 2025 to investigate the effect of AI-driven credit grading on loan default rates in Nigeria's digital lending ecosystem.then employed logistic regression and panel Ordinary Least Squares (OLS) approaches to assess the association between AI adoption and credit performance, and then anchored the investigation using the Information Asymmetry Theory and Financial Intermediation Theory. The results demonstrate that, in comparison to conventional models, the AI-based credit scoring considerably lowers the default likelihood by roughly 18–24%. Predictive accuracy is positively and statistically significantly impacted by alternative data utilization. However, these benefits are moderated by the level of regulatory compliance.

In their study of AI-based credit scoring tools in rural Nigeria, Babarinde et al. (2025) discovered that machine learning models utilizing utility bills, mobile transactions, and behavioral patterns greatly enhance smallholder farmers' creditworthiness assessments, improving loan access and lowering defaults through platforms such as carbon. Furthermore, Agu et al. (2024) looked into predictive analytics in banks and showed how Al algorithms like decision trees and neural networks lower credit risk using unconventional data like social media activity, allowing for more accurate lending and prompt repayment issue detection among underbanked segments. These methods are also supported by micro-level data from Nigerian banks:

Al integration in commercial banks for credit risk management, including borrower and predictive analysis, process minimization, and non-performing loans, were expounded upon by Benjamin et al. (2024). According to Adepetun et al. (2022), using machine learning improves credit risk assessment by predicting borrower behavior and reducing biases, which improves repayment performance. Others have also looked into the environmental and sectoral aspects of Al in Nigerian banking, with variable results according on local conditions and implementation. Using bibliometric analysis of Al trends in African finance services, Moela et al. (2024) demonstrated the wide range of applications in credit risk prediction, including neural networks to evaluate non-performing loans in Nigeria, where Al promotes stability and accessibility while economic volatility affects loan provisions.

Studies conducted at the national level in Nigeria (Benjamin et al., 2024; Adepetun et al., 2022) show that the use of Al in risk reporting and model validation is positively correlated with financial innovation, lowering default rates since results are affected by heterogeneity in data quality: Brown (2024) shown that although machine learning performs better than conventional techniques in pattern detection, its influence on loan repayment depends on hybrid human-Al approach. In Moela et al. (2024), cross-regional heterogeneity emphasizes that impacts vary by setting (e.g., Nigeria versus other African countries) and makes the case for segmenting Al applications when examining banking performance and repayment efficiency.

Institutional, operational, and perceptual limitations controlling these benefits have been examined in a parallel thread. Algorithmic bias, data privacy, infrastructure flaws, and a lack of transparency have all been identified in criticisms and evaluations (Agu et al., 2024; Babarinde et al., 2025) as impeding Al spread inside Nigerian banking. The accuracy of credit assessments is hampered by operational frictions such as low data quality and regulatory loopholes, which are recognized by empirical analysis (Adepetun et al., 2022; Brown, 2024). Adoption heterogeneity research (Benjamin et al., 2024; Moela et al., 2024) identify ethical and demographic problems that require focused education and governance. Lastly, research that looks ahead (Agu et al., 2024; Babarinde et al., 2025) points to explainable Al and regulatory frameworks as possible facilitators, but that inclusive effects on loan payback require infrastructure, equity, and cooperation. Overall, the literature shows promise, but it also suggests that, in the Nigerian context, effects would depend on ethical design, data governance, and policy coordination.

The impact of big data analytics on credit risk assessment in small and medium-sized firm (SME) lending was examined by Wong and Chan (2019). The researchers used a mixed-methods approach, combining qualitative interviews with SME loan officers with quantitative analysis of loan performance data. According to their research, banks that used big data analytics were able to evaluate credit risk for SME loans more accurately. They found connections and trends in SME financial data that were frequently missed by conventional techniques. In order to improve credit risk assessment procedures in SME financing, the researchers suggested making more investments in big data infrastructure and analytics capabilities.

In order to evaluate the use of machine learning methods in credit risk assessment, Schmidt and Mueller (2017) surveyed European banks. They gathered information on the kinds of machine learning models employed, difficulties faced, and perceived advantages through the survey. The results showed that European banks are increasingly using machine learning for credit risk assessment. However, obstacles to widespread application were noted, including problems with data quality and interpretability of the model. In order to resolve these problems and encourage the responsible application of machine learning in credit risk assessment, the researchers suggested that banks and regulatory bodies work together.

Harper and Lewis (2018) examined how artificial intelligence affected the credit rating algorithms that banks in North America employed. In addition to analyzing loan performance data and model validation criteria, their study contrasted conventional statistical methods with artificial intelligence approaches. According to the results, banks that used artificial intelligence in their credit scoring algorithms outperformed conventional methods in terms of predicted accuracy and default rates. When it came to identifying intricate patterns of credit risk, machine learning systems performed better. In order to effectively utilize artificial intelligence's potential in credit risk assessment, the report advised North American banks to invest in infrastructure and personnel development.

2.3 Theoretical Framework

This study is framed by agency theory, which states that lenders (principals) assign screening and monitoring to bank officials and automated systems (agents), resulting in information asymmetry and monitoring expenses (Jensen & Meckling 1976). Al serves as a technology that improves governance. Predictive analytics and automated underwriting increase monitoring accuracy and frequency, while algorithmic scoring can lessen biased human judgment. However, agency gains are contingent upon genuine deployment, incentive alignment, and the ability to respond to signals. Officers' reliance on Al outputs is determined by perceived utility (accuracy, speed) and perceived simplicity of use (explainability, integration), according to the Technology Acceptance Model (TAM) (Davis, 1989).

Al's use of alternative data is important in markets with few formal credit records because information-economics (Akerlof, 1970) indicates that richer signals improve screening and monitoring by reducing moral hazard and adverse selection. Heterogeneity among bank types is explained by diffusion of innovations and institutional theory: adoption and routinization are influenced by relative advantage, compatibility, regulatory pressures, and organizational norms (Rogers, 2003; DiMaggio & Powell, 1983). These threads are connected by a socio-technical synthesis: organizational practices, attitudes, and technology affordances combine to produce results. According to the study's hypothesis, adoption of AI enhances the quality of credit assessments and, depending on perceptions of fairness and organizational capacity, lowers delinquency and defaults through mediated institutional behaviors. The results will help bank managers and legislators create AI applications that significantly enhance financial stability and credit discipline.

3. METHODOLOGY

The factors influencing Nigerian microfinance institutions' adoption of Artificial Intelligence (AI), Credit Assessment (CA), and Loan Repayment (LR) are investigated in this study using a quantitative cross-sectional survey research design. Credit officers, compliance/regulatory personnel, and retail customers are asked to complete a questionnaire that provides them with first-hand information on their bank's credit evaluation and loan payback. In order to provide sufficient statistical power for Partial Lease-Structural Equation Modeling (PLS-SEM) and to allow for variance-based SEM (VB-SEM) tests in the event that distributional assumptions are valid and sample size requirements are met, 125 microfinance employees were purposefully sampled. A structured questionnaire using a five-point Likert response scale (1 being strongly disagree and 5 being strongly agree) is used to collect primary data.

Six reflecting indicators are used in the measure to operationalize Al, six reflective indicators for credit assessment, and five indicators for loan repayment. The adoption survey questions were modified from Li & Jin (2024) and Almaiah et al. (2022). The credit assessment questions were modified from Tsai (2016) and Thomas (2000). Endris (2022) and a recent empirical study on loan payback behavior for digital lending platforms (2025) served as the model for the loan repayment scale. Due to its moderate sample size, flexibility in managing reflective measures, and applicability for prediction models, the analytical technique is equivalent to PLS-SEM with SPSS ADANCO.

4. RESULT AND DISCUSSION

4.1 Respondents' Profiles

The sample distribution of respondents' profiles is displayed in Table 1. Male respondents made up 52.8% of the total respondents, while female respondents made up 47.2%. This indicates that male respondents make up the largest percentage of respondents.

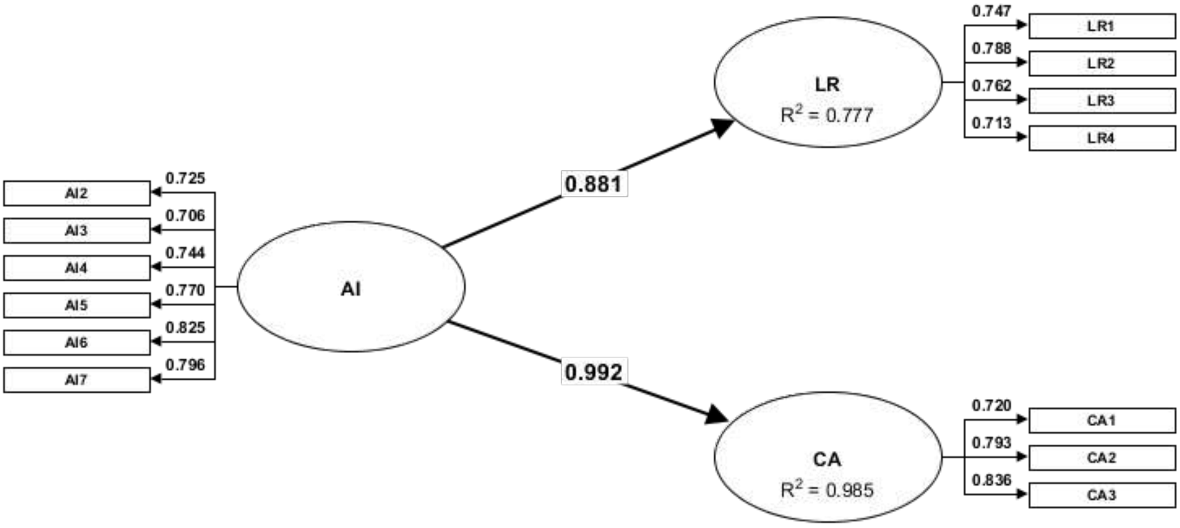
Table 1: Demography of the Respondents

1	**Gender of the respondents**	**Frequency**	**Percentage %**
	Male	66	52.8
	Female	59	47.2
	Total	**125**	**100**
3	**Age of the respondents**	**Frequency**	**Percentage %**
	18-27 years old	58	46.4
	28-37 years old	45	36.0
	38-47 years old	16	12.8
	48 years and above	6	4.8
	Total	**125**	**100**
4	**Educational Level**	**Frequency**	**Percentage %**
	primary/secondary school	18	14.4
	NCE/ND	84	67.2
	HND/Degree	14	11.2
	Postgraduate	9	7.2
	Total	**125**	**100.0**

The profiles of respondents in respect to age are described as 46.4% are those within the age of 18 to 27 years old, 36% are those between the age of from 28 to 37 years old, 12.8% are those within the age from 38 to 47 years old, while, those within the age of above 48 years old constituted 4.8%. Based on this result majority of the respondents falls between from 18 to 27 years old. In respect of the educational level of the respondents in Table 1 14.4% respondents hold primary/secondary, 67.2% are those respondents with National Certificate for Education(NCE)/ National Diploma (ND), 11.2% of the respondents were Higher National Diploma (HND)/ University degree, while 7.2% are posgraduate it is concluded that most of the respondents are with NCE/ND..

4.2 Measurement models

The measurement models for Artificial Intelligence Adoption (AI), Loan Repayment (LR), and Credit Assessment (CA) were computed using the indicators discovered in the exploratory factor analysis. Indicators that showed statistical and behavioral importance in PLS-SEM were retained in the final models after a comprehensive hypothesis test. The results from the measurement model components are covered in this section. Verifying the model's scale validity and reliability is the typical process for SEM analysis. The fitness index and coefficient of determination are used to assess the suitability of the measurement model and structural model. The fitness measure used to evaluate how well the model fits the available data is called Standardized Root Mean Residual, or SRMR. The more adequate the model is with the data, the lower the SRMR value, which is often advised below 0.08. The SRMR value generated in this instance is 0.0571, which is much less than the suggested value.



The composite reliability coefficients over the 0.70 threshold value were used to verify the model's reliability (see Table 2 and Figure 1). Because all of the remaining items are above 0.70 of composite loading, each construct's item generates strong internal consistency. The Average Variance Extracted (AVE) was used in confirmatory composite analysis, which is a component of a PLS-PM study, for the convergent validity. After removing five items, the results indicate that the majority of items have a standardized composite loading that greatly surpasses the required minimum of 0.70. Following the removal of the two items from the model, none of the built AVE experiences fell below the 0.50 cut-off. Given that the numbers fall between 0.5669 and 0.6149, this supports the measurement model's convergent validity. As a result, for these constructs, the variation acquired from their item is greater than the mistake variance. The convergent validity results are shown in Table 2.

Table 2: Construct Reliability, Average variance extracted (AVE) and Variance inflation factors (VIF)

Construct		**Dijkstra-Henseler's rho (ρ_A)**	**Jöreskog's rho (ρ_c)**	**Cronbach's alpha(α)**	**Average variance extracted (AVE)**	VIF
AI		**0.8942**	**0.8924**	**0.8929**	**0.5810**	
AI2	0.7247					**2.0753**
AI3	0.7062					**2.5420**
AI4	0.7444					**3.2375**
AI5	0.7704					**1.8844**
AI6	0.8251					**2.8267**
AI7	0.7959					**1.8611**
LR		**0.8405**	**0.8395**	**0.8390**	**0.5669**	
LR1	0.7475					**1.7355**
LR2	0.7875					**2.1934**
LR3	0.7623					**1.7579**
LR4	0.7125					**1.8015**
CA		**0.8307**	**0.8268**	**0.8247**	**0.6149**	
CA1	0.7195					**1.6544**
CA2	0.7928					**1.9980**
CA3	0.8358					**2.1394**

4.3 Structural Model

The coefficient of determination, R2, and path coefficients are analyzed using the PLS-PM in relation to the structural model practice. Due to the conventional least squares estimator's limitations, the PLS-PM approach requires a bootstrap procedure in order to produce the standard error of path coefficients (McDonald & Ho., 2002; Ronkko & Evermann, 2013; Aimran et al., 2017). In accordance with the findings of Sarstedt et al. (2019) and Henseler, Hubona, & Ray (2016), 4,999 resampling is advised to improve an estimate's degree of precision and consistency.

The redundancy of endogenous constructs and model validity are typically verified by testing the Stone-Geisser's Q2 and goodness of fit (GoF). However, it has been demonstrated that these metrics are insufficient in PLS-PM (Henseler & Sarstedt, 2013; Henseler & Dijkstra, 2015). Therefore, these evaluations are not used in the structural model in this study. Lastly, the model's overall variance is explained using the coefficient of determination, or R2. According to the R2 values, AI has explained 77.66% of the loan repayment variance and 98.49% of the credit evaluation variance. This value is at the satisfactory levels because it is greater than 0.10, as recommended by Hair et al. (2014) and Falk & Miller (1992). However, the moderate percentage of 30.8% of unexplained variations suggests that the explanatory power of the customer satisfaction construct can be increased by additional significant elements that are outside the purview of this study.

4.4 Direct Effect

Examining the research hypotheses comes next, following the validation of the measurement assessment and structural model. At the significant threshold of 0.05, the PLS-PM technique results (AI -> LR, $\beta = 0.8813$, $t = 12.5758$, p-value = 0.000) offer strong support for the untested hypothesis. With a standardized regression weight of 0.8813, which is greater than half of the overall effect of 0.50, the AI has a comparatively strong impact on loan repayment. The results of this study are consistent with those of Aladejubelo's (2026) study, which confirmed that AI-based credit scoring dramatically lowers default likelihood by roughly 18–24% when compared to conventional models. Likewise, (AI -> CA, $\beta = 0.9924$, $t = 31.5352$, p-value = 0.000). With a normalized regression weight of 0.9924, which is greater than half of the overall effect of 0.50, the AI has a comparatively high significant impact on credit evaluation. The results of this study are in line with research by Babarinde et al. (2025), which shows that AI integration in commercial banks for credit risk management, including borrower and predictive analysis, decreasing procedures and non-performing loans. Table 3 displays the direct effect outcome.

Table 3: Hypotheses testing

Effect	Original coefficient	Standard bootstrap results			
		Mean value	Standard error	t-value	p-value
AI -> LR	0.8813	0.8855	0.0701	12.5758	0.0000
AI -> CA	0.9924	0.9939	0.0315	31.5352	0.0000

5. CONCLUSIONS

In conclusion, AI is changing credit risk assessment by improving accuracy, broadening loan availability, and streamlining financial sector operations. Although there are many advantages to these developments, there are also issues with transparency, morality, and legal compliance. Financial institutions must strike a balance between innovation and accountability in order to fully realize the potential of AI, making sure that AI applications are clear, equitable, and compliant with consumer protection regulations. A more open financial environment will be supported and credit evaluation will continue to change as a result of the continued cooperation between traditional banks and fintech as well as new technology.

In the long run, the financial industry's use of artificial intelligence has the potential to completely change how operations and risks are handled as well as how financial institutions interact with their clients. AI has the potential to be a crucial instrument for promoting trust and transparency in a financial ecosystem that is becoming more and more digitalized, as long as organizations give ethical and responsible use of the technology first priority. Furthermore, by enabling underprivileged populations to obtain finance and promoting financial inclusion on a broader scale, the integration of AI might significantly contribute to the reduction of global economic inequities. The success of this shift, nonetheless, depends on institutions' capacity to strike a balance between innovation and consumer protection as well as to create adaptable regulatory frameworks that can keep up with the quick advancement of technology. Finding this balance will determine whether AI promotes sustainable economic growth or exacerbates already-existing disparities by causing economic polarization.

6. RECOMMENDATIONS

Suggestions Regarding Artificial Intelligence's Impact on Credit Risk Evaluation in Nigerian Microfinance Banks

i. To improve the theoretical knowledge of AI-driven credit risk assessment models, make ongoing investments in research and development. In order to more accurately forecast borrower behavior and default rates, this involves investigating the integration of machine learning with behavioral economics theories. Furthermore, encouraging multidisciplinary cooperation across computer science, behavioral sciences, and finance might result in novel theoretical frameworks that take into consideration the dynamic character of credit risk assessment in a financial environment that is changing quickly.

ii. Urge banks to use a hybrid strategy that blends human knowledge with the advantages of AI-driven models. Human judgment is crucial for evaluating results, comprehending contextual subtleties, and making well-informed judgments, even though AI algorithms are excellent at processing enormous volumes of data and spotting patterns. Consequently, banks ought to give top priority to the creation of human-AI collaborative systems that make use of the complementing capabilities of both humans and machines in credit risk assessment procedures.

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