AI-Driven Credit Scoring Systems and Financial Inclusion in Emerging Markets

IBORO AKPAN ESSIEN[1], GERALDINE CHIKA NWOKOCHA[2], ESEOGHENE DANIEL ERIGHA[3], EHIMAH OBUSE[4], AYORINDE OLAYIWOLA AKINDEMOWO[5]

[1]*Mobil Producing Nigeria Unlimited, Eket, Nigeria*

[2]*Slot Engineering, Nigeria*

[3]*Senior Software Engineer, Eroe Consulting,Dubai, UAE*

[4]*Lead Software Engineer, Choco, Berlin, Germany*

[5]*Patricia Technologies, Vilnius, Lithuania*

Abstract- Artificial Intelligence (AI)-driven credit scoring systems are rapidly transforming the financial landscape in emerging markets, offering promising solutions to address long-standing challenges of financial exclusion. Traditional credit assessment models, which rely heavily on formal credit histories and collateral, often fail to accommodate low-income individuals, informal workers, and micro-entrepreneurs who lack access to formal banking systems. AI-powered credit scoring leverages alternative data sources such as mobile phone usage, digital payment histories, utility bills, social media activity, and psychometric profiles to evaluate creditworthiness. By applying machine learning algorithms and predictive analytics, these systems can identify credit risks with greater speed, accuracy, and inclusiveness than conventional models. This explores the role of AI-driven credit scoring in promoting financial inclusion in emerging markets. It examines the technological foundations of these systems, highlighting how alternative data and AI techniques such as neural networks and decision trees are used to create dynamic, adaptive credit models. This also analyzes the key opportunities these systems present, including expanded credit access for underserved populations, reduced loan processing times, and the development of personalized credit products suited to diverse financial needs. However, this also addresses significant risks and challenges, including concerns over data privacy, algorithmic bias, lack of transparency in AI decision-making, and regulatory gaps in emerging markets. To mitigate these risks, this recommends best practices such as ethical AI guidelines, fairness audits, robust data governance, and explainable AI tools. Finally, it outlines future directions, including cross-sector collaboration, investment in digital literacy, and the creation of global standards for responsible AI credit scoring. This concludes that while AI-powered credit scoring systems offer substantial potential to foster financial inclusion, their success depends on balancing innovation with fairness, accountability, and regulatory oversight to ensure equitable and sustainable financial access in emerging markets.

Index Terms- AI-driven, Credit scoring systems, Financial inclusion, Emerging Markets

I. INTRODUCTION

Financial exclusion remains one of the most persistent barriers to economic development in emerging markets, affecting millions of individuals and small businesses (Mustapha *et al*., 2018; Oyedokun *et al*., 2019). A significant proportion of the population in low- and middle-income countries lacks access to formal financial services, including credit (Olaoye *et al*., 2016; SHARMA *et al*., 2019). According to the World Bank's Global Findex Database, nearly 1.4 billion adults globally remain unbanked, with the majority residing in Africa, Asia, and Latin America. In many cases, low-income individuals, micro-entrepreneurs, and informal workers face structural obstacles to obtaining credit, including unstable incomes, lack of formal employment, and the absence of verifiable credit histories (Oduola *et al*., 2014; Akinluwade *et al*., 2015). Traditional credit scoring systems, which depend on borrowers' past interactions with formal financial institutions, often fail to capture the financial behaviors and capacities of such underserved populations. Moreover, conventional lending models typically require collateral or guarantors, further excluding those who lack significant assets or formal financial relationships (Raj and Raman, 2017; Attaran *et al*., 2018).

Against this backdrop, Artificial Intelligence (AI)-driven credit scoring has emerged as a transformative solution. By leveraging alternative data sources such as mobile phone usage patterns, digital payment records, e-commerce transactions, utility payment histories, and even social media activity, AI-based models are capable of assessing the creditworthiness of individuals previously deemed "unscorable" by conventional methods (Balaraman and Chandrasekar, 2016; Guo *et al*., 2018). In many emerging markets, mobile phones and digital payment systems have become deeply integrated into daily life, producing vast amounts of transactional and behavioral data. AI and machine learning (ML) algorithms analyze these data points to detect patterns, predict repayment behaviors, and assign credit scores with far greater flexibility than traditional models. Techniques such as decision trees, neural networks, and ensemble learning enable lenders to process large datasets, continuously refine risk assessments, and extend credit to underserved populations more effectively.

The growing adoption of AI-driven credit scoring systems in emerging markets is not only redefining credit access but also reshaping the broader financial inclusion landscape (Gomber *et al*., 2018; Gozman *et al*., 2018). Financial technology (fintech) firms, microfinance institutions, and even traditional banks are increasingly integrating AI tools to expand their lending operations to low-income and informal sector borrowers. These technologies offer several potential benefits, including faster loan processing, cost-efficient risk evaluation, and more inclusive credit access. Additionally, AI-powered credit scoring enables the development of personalized loan products tailored to individual repayment capacities, thereby fostering responsible borrowing and financial resilience (Riikkinen *et al*., 2018; Dhanabalan and Sathish, 2018).

Despite their transformative potential, AI-driven credit scoring systems also raise significant concerns. Issues such as data privacy, cybersecurity, algorithmic bias, and lack of transparency in decision-making pose complex challenges, particularly in regulatory environments that may be underdeveloped or fragmented. Without adequate oversight, these technologies could unintentionally reinforce existing inequalities or expose vulnerable populations to predatory lending practices. Therefore, it is essential to carefully assess the balance between technological innovation and consumer protection in the context of AI-powered financial services.

The purpose of this, is to provide a comprehensive analysis of the role of AI-driven credit scoring systems in advancing financial inclusion in emerging markets. It will explore the technological foundations and data sources that underpin these systems, evaluate the key opportunities they present for expanding credit access, and examine the potential risks and challenges associated with their deployment. Furthermore, this will outline best practices and future directions to ensure that AI-driven credit scoring contributes to equitable and sustainable financial systems.

In doing so, this seeks to offer actionable insights for policymakers, financial institutions, technology developers, and development practitioners seeking to harness AI-powered credit scoring responsibly. Ultimately, this argues that while AI-based credit scoring represents a significant leap forward in promoting financial inclusion, its success depends on striking a careful balance between innovation, fairness, transparency, and regulatory oversight. Through a nuanced approach, emerging markets can leverage these technologies to unlock new pathways toward inclusive economic growth and financial empowerment (Khosla *et al*., 2017; Vu and Hartley, 2018).

II. METHODOLOGY

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology was applied to ensure a transparent, comprehensive, and replicable review process for this on AI-driven credit scoring systems and financial inclusion in emerging markets. A systematic search strategy was designed to identify relevant peer-reviewed journal articles, conference papers, institutional reports, and working papers published between January 2013 and June 2025. Databases searched included Scopus, Web of Science, IEEE Xplore, ScienceDirect, and Google Scholar. Additionally, grey literature sources such as World Bank, International Monetary Fund (IMF), Consultative Group to Assist the Poor (CGAP), and reports from financial technology (fintech) associations were included to capture emerging insights from non-academic sources.

Keywords and Boolean operators were combined to maximize search coverage. Key search terms included "AI credit scoring," "machine learning credit assessment," "financial inclusion," "alternative data," "emerging markets," "digital finance," "algorithmic lending," "fintech," and "financial technology." Search filters were applied to include only English-language sources focusing on low- and middle-income countries, particularly in regions such as Sub-Saharan Africa, South Asia, Southeast Asia, and Latin America.

The initial search yielded 1,426 records. After the removal of duplicates, 1,092 studies remained. Titles and abstracts were screened to exclude studies unrelated to credit scoring, AI applications, or financial inclusion, which reduced the pool to 238 potentially relevant sources. These records underwent full-text review based on predefined inclusion criteria: (1) focus on AI or machine learning in credit assessment, (2) explicit discussion of financial inclusion or credit access in emerging markets, and (3) empirical evidence or conceptual analysis of AI-driven credit scoring models.

Following the full-text review, 87 studies met the inclusion criteria. Data were extracted systematically, covering study objectives, methodology, geographic focus, data sources, AI techniques, outcomes related to credit access, and identified risks or challenges. Studies were then synthesized thematically to identify key trends, opportunities, and limitations. Disagreements regarding study inclusion were resolved through consensus among the reviewers to ensure methodological rigor.

2.1 Overview of AI-Driven Credit Scoring Systems

The rapid proliferation of digital technologies and financial innovations has led to a paradigm shift in the credit assessment landscape, particularly within emerging markets. AI-driven credit scoring systems are increasingly regarded as transformative tools for expanding financial access among previously excluded populations (Bisht and Mishra, 2016; Peck and Whiteside, 2016). These systems utilize advanced computational models and diverse data sources to evaluate an individual's creditworthiness, offering distinct advantages over traditional credit scoring methods. This provides a comprehensive overview of the definition, mechanisms, data sources, and comparative benefits of AI-driven credit scoring systems.

AI-driven credit scoring refers to the application of artificial intelligence (AI) and machine learning (ML) algorithms to evaluate the creditworthiness of individuals or businesses. Unlike traditional models that rely primarily on historical credit bureau data, AI-driven systems analyze a wide array of alternative data points to generate dynamic and predictive credit assessments. These systems employ a variety of machine learning techniques, including supervised learning, unsupervised learning, and reinforcement learning, to identify patterns in large datasets and make risk-based predictions (Tzanakou, 2017; Saravanan and Sujatha, 2018).

Machine learning algorithms are central to AI-based credit scoring. These algorithms are trained using labeled datasets that contain known instances of credit defaults and successful repayments. Through iterative learning processes, ML models—such as decision trees, random forests, gradient boosting machines, and support vector machines—develop the capacity to predict future credit outcomes. Neural networks, particularly deep learning architectures, are also increasingly utilized for complex credit modeling tasks, especially in cases where large volumes of nonlinear, high-dimensional data are involved.

Predictive analytics forms the backbone of AI-driven credit scoring systems. By identifying correlations between diverse behavioral and transactional variables, these systems can forecast the likelihood of loan repayment or default. AI models are capable of adapting over time as they are continuously exposed to new data, enabling them to refine risk assessments and detect emerging credit trends with high precision (Bughin *et al*., 2017; Yeung, 2018). This adaptability makes AI-driven credit scoring particularly valuable in volatile or rapidly changing financial environments, such as those common in emerging markets.

A defining feature of AI-driven credit scoring systems is their ability to leverage non-traditional, alternative data sources. These include digital footprints that are often readily available in emerging markets, even among unbanked or underbanked populations. The following categories represent the key data sources utilized in such systems; Mobile usage data—such as call frequency, SMS patterns, data consumption, geolocation, and airtime top-up history—provides valuable insights into a borrower's behavior and financial reliability. In many emerging markets, where mobile penetration rates surpass those of formal banking services, mobile phone metadata offers a rich and accessible dataset for credit scoring (Goyal, 2017; Kanobe *et al*., 2017).

Payment records from utility providers (e.g., electricity, water, gas) serve as proxies for financial responsibility and payment consistency. Timely payments of utility bills are considered strong indicators of a borrower's ability and willingness to meet credit obligations.

Digital payments, e-commerce activity, and mobile money transactions offer detailed insights into an individual's spending habits, income flows, and financial management capabilities. Fintech platforms and mobile money operators frequently integrate these data into AI models to assess creditworthiness.
Behavioral patterns inferred from social media platforms—such as network connections, posting frequency, and engagement—are increasingly being explored for credit scoring purposes (Wei *et al*., 2016; Rathore *et al*., 2017). Although this remains controversial due to privacy concerns, some studies suggest that social media behaviors can correlate with financial trustworthiness.

Psychometric assessments involving questionnaires about personal traits, financial attitudes, and cognitive abilities can be digitized and analyzed using AI models. These tests capture qualitative factors such as risk aversion, integrity, and problem-solving skills, which are difficult to observe through traditional financial metrics but are relevant for credit evaluations.

The integration of such diverse data sources enables AI-driven systems to generate more comprehensive and nuanced credit profiles, particularly in settings where conventional financial data is sparse or absent.
AI-driven credit scoring systems present several distinct advantages over traditional credit scoring methods, which rely largely on formal credit histories, loan repayment records, and income documentation (Cash, 2018; Zamore *et al*., 2018). The key comparative benefits include; AI-powered models can process vast datasets in real time, delivering instant credit decisions. Traditional models often require manual verification processes that may take days or weeks, limiting their efficiency in fast-paced lending environments.
By analyzing a broader spectrum of variables, AI models achieve higher predictive accuracy than traditional systems. They can identify subtle behavioral patterns and non-linear relationships that traditional statistical models may overlook.
AI credit scoring platforms are highly scalable, capable of handling millions of applications simultaneously without significant increases in operational costs (Alhaddad, 2018; Qi and Xiao, 2018). This is particularly important for microfinance institutions and fintech lenders targeting large underserved populations in emerging markets.

AI models are adaptable to evolving market conditions and borrower behaviors. They can be retrained with new data to improve predictive performance, unlike traditional models that often require periodic manual recalibration. Traditional credit scoring systems systematically exclude individuals without formal financial histories. In contrast, AI-driven models utilize alternative data to provide credit access to previously unscorable populations, promoting greater financial inclusion.
Despite these advantages, it is essential to acknowledge potential challenges, such as

algorithmic bias and data privacy risks, which may arise in the deployment of AI-based systems. Nonetheless, the overall comparative benefits underscore the transformative potential of AI-driven credit scoring in enhancing the reach, efficiency, and inclusiveness of credit markets in emerging economies (Anderson *et al*., 2017; Choi and Park, 2017).

AI-driven credit scoring systems represent a significant advancement in the evolution of credit assessment practices. By integrating machine learning algorithms with diverse, alternative data sources, these systems can generate rapid, accurate, and inclusive credit evaluations, addressing many of the structural limitations inherent in traditional credit models. Their scalability and flexibility make them particularly well-suited for emerging markets, where financial exclusion remains widespread. As these technologies continue to evolve, they offer a promising pathway for promoting financial inclusion and expanding credit access to underserved communities worldwide (Arner *et al*., 2018; Lumsden, 2018).

2.2 Opportunities for Financial Inclusion

The advent of artificial intelligence (AI)-driven credit scoring systems has opened new avenues for promoting financial inclusion in emerging markets. In contexts where traditional credit evaluation mechanisms fail to adequately serve large segments of the population, AI-based credit models offer a transformative approach to expand credit access, reduce the costs and time of credit decision-making, and personalize credit offerings (Mittelstadt *et al*., 2016; Raso *et al*., 2018). These innovations are particularly relevant for low-income individuals, informal workers, and small businesses that have historically been excluded from formal financial services due to a lack of collateral, formal employment records, or credit histories as shown in figure 1. This explores the key opportunities offered by AI-driven credit scoring in fostering financial inclusion.

One of the most significant contributions of AI-powered credit scoring systems lies in their ability to extend credit access to underserved populations. Traditional credit scoring relies heavily on formal financial histories, such as loan repayment records, salary slips, and banking transactions, which are often unavailable to low-income individuals, informal workers, and micro, small, and medium enterprises (MSMEs) in emerging markets. According to the International Finance Corporation (IFC), over 65 million firms in developing economies face credit constraints, largely due to the inability to meet conventional lending criteria.

AI-driven credit scoring overcomes these limitations by using alternative data sources such as mobile phone usage patterns, utility payments, digital transactions, and psychometric assessments. These data points offer valuable insights into an individual's financial behavior, reliability, and risk profile, even in the absence of formal credit histories. As a result, lenders can assess creditworthiness more inclusively, enabling previously excluded individuals and enterprises to access loans and other financial products (Campen, 2016; Iwasaki, 2018; Olanrewaju, 2018).

Figure 1: Opportunities for Financial Inclusion

In countries where mobile penetration exceeds traditional banking access, such as Kenya, India, and Nigeria, AI-powered credit scoring linked to mobile money platforms has dramatically expanded access to microloans and digital credit. By democratizing access to credit, these systems empower low-income households to invest in essential needs such as education, healthcare, and income-generating activities. Furthermore, small businesses can use these funds to purchase inventory, invest in equipment, or expand operations, driving broader economic growth and poverty reduction (Taiwo and Falohun, 2016; Mbuyisa and Leonard, 2017).

Another critical opportunity provided by AI-driven credit scoring is the significant reduction in the time and cost associated with credit decision-making. Traditional loan approval processes often involve lengthy documentation reviews, in-person interviews, and manual risk assessments, leading to high operational costs and slow disbursement timelines (Green *et al*., 2017; Mostaan and Ashuri, 2017). Such delays disproportionately affect small-value loans, where the administrative costs may exceed potential returns, thereby discouraging lenders from serving low-income or small-scale borrowers.

AI-powered credit models automate many aspects of the credit evaluation process. Machine learning algorithms can instantly process and analyze vast amounts of data to predict credit risk, enabling lenders to make near-real-time loan decisions. This automation is particularly beneficial for microloans and nano-credit products, which involve relatively small loan amounts but high transaction volumes.

Fintech companies and digital lenders have leveraged this capability to introduce instant or same-day credit products targeted at underserved populations. Platforms such as Tala, Branch, and M-Shwari in Africa, as well as similar models in South Asia and Latin America, utilize AI to deliver automated credit decisions within minutes of application submission. These services have reduced barriers to credit by streamlining the approval process, lowering operational costs, and increasing the scalability of lending services.

Moreover, faster credit disbursement is vital for borrowers facing urgent liquidity needs, such as medical emergencies or unforeseen business expenses. By enabling immediate access to funds, AI-driven systems enhance financial resilience among vulnerable populations and reduce dependence on informal moneylenders who often charge exorbitant interest rates.

AI-based credit scoring also enables the development of personalized credit products that better match the specific needs and capacities of borrowers. Traditional credit products are typically standardized, with uniform loan terms, repayment schedules, and interest rates that may not reflect the financial realities of diverse borrower groups (Mills and McCarthy, 2016; Obiora and Csordás, 2017). Such standardization can lead to either credit exclusion or high default rates when borrowers are unable to meet rigid repayment conditions.

AI-driven credit scoring leverages behavioral data, including spending patterns, cash flow variability, and risk preferences, to tailor credit offerings. By analyzing these data points, lenders can customize loan terms such as repayment frequency, loan duration, interest rates, and credit limits to align with individual borrower profiles.

For example, smallholder farmers with seasonal income streams can be offered flexible repayment schedules that coincide with harvest periods, reducing the likelihood of loan defaults. Similarly, micro-entrepreneurs operating in volatile markets may benefit from dynamic credit lines that adjust based on cash inflows and business performance.
Personalized credit products not only improve repayment performance but also promote responsible borrowing by ensuring that borrowers take on manageable debt levels. Furthermore, as AI models continuously learn from borrower behavior, lenders can refine product offerings over time to enhance suitability and financial outcomes for clients.

Additionally, personalization fosters long-term customer engagement and loyalty. Borrowers who experience positive credit interactions are more likely to continue using formal financial services, thereby deepening financial inclusion and encouraging broader financial ecosystem participation, such as savings, insurance, and digital payments.

AI-driven credit scoring systems present transformative opportunities for advancing financial inclusion in emerging markets. By expanding credit access to underserved groups—such as low-income individuals, informal workers, and small businesses—these systems address key structural barriers inherent in traditional lending models (Sapovadia, 2018; Mujeri and Azam, 2018). The automation of risk assessment processes dramatically reduces credit decision time and operational costs, making it economically viable for lenders to offer microloans and nano-credit products. Furthermore, AI's capacity to customize credit products based on behavioral and transactional data enables more personalized, flexible, and borrower-centric financial services.

These innovations not only improve access to credit but also promote financial resilience, entrepreneurship, and poverty reduction. However, to fully realize these benefits, it is essential to address challenges related to data privacy, algorithmic fairness, and regulatory oversight. Nonetheless, the opportunities presented by AI-powered credit scoring systems mark a significant step toward more inclusive, efficient, and responsive financial systems in emerging markets. As digital infrastructure continues to expand, these technologies are poised to play an increasingly central role in shaping the future of financial inclusion worldwide.

2.3 Key Challenges and Risks

While AI-driven credit scoring systems offer transformative potential to expand financial inclusion in emerging markets, their deployment also presents substantial challenges and risks. As these technologies become more integrated into lending processes, concerns have emerged regarding data privacy and security, algorithmic bias and fairness, transparency and explainability, and regulatory and legal uncertainties as shown in figure 2. Failure to address these challenges may not only undermine trust in AI-based credit systems but also perpetuate or exacerbate socio-economic inequalities (Duderstadt, 2016; Jabłonowska *et al*., 2018).

One of the foremost risks associated with AI-driven credit scoring systems involves data privacy and security. These systems rely heavily on large volumes of sensitive personal data, including mobile phone metadata, social media activity, transaction records, and psychometric profiles. Many of these data points are not traditionally considered in financial transactions, raising ethical concerns about the scope of data collection and potential misuse.
In emerging markets, where data protection laws are often underdeveloped or inconsistently enforced, the risks of unauthorized data sharing, breaches, and exploitation are significant. Without robust safeguards, sensitive financial and behavioral information can be exposed to cyberattacks or misappropriated by third-party entities, potentially leading to identity theft, financial fraud, or discriminatory targeting.

While global regulations such as the European Union's General Data Protection Regulation (GDPR) have set high standards for data protection, many emerging economies are still in the process of developing comprehensive legal frameworks for data privacy. Countries such as Kenya, Nigeria, and India have begun introducing data protection laws, but enforcement mechanisms often remain weak, leaving consumers vulnerable.

Furthermore, many borrowers in emerging markets have limited awareness of data rights and privacy risks. They may consent to data sharing without fully understanding the implications, particularly when facing urgent credit needs. As a result, lenders and fintech firms face growing pressure to implement transparent data governance practices, ensure informed consent, and adopt privacy-preserving technologies, such as data anonymization and encryption.

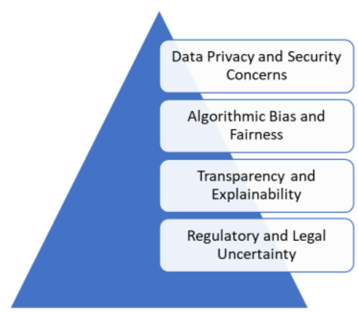

Figure 2: Key Challenges and Risks

Another critical risk in AI-driven credit scoring relates to algorithmic bias and fairness. Machine learning models are trained on historical datasets that may already contain social, economic, and institutional biases. If these biases are not carefully mitigated, AI systems can reinforce existing inequalities by systematically disadvantaging certain groups based on gender, ethnicity, geography, or socio-economic status.

For instance, if a training dataset disproportionately represents male urban borrowers, the resulting credit model may assign lower scores to female borrowers or rural applicants, even if their creditworthiness is comparable. Similarly, models using mobile phone data may penalize individuals with limited access to digital services, further marginalizing those who already face barriers to formal financial systems.

This risk is particularly acute in emerging markets, where structural inequalities—such as gender disparities in phone ownership, regional gaps in digital infrastructure, and informal employment patterns—are widespread. Without proactive measures to detect and mitigate bias, AI credit scoring systems may inadvertently deepen financial exclusion.

Ensuring fairness in AI models requires rigorous testing, including fairness audits, demographic parity assessments, and algorithmic impact evaluations. Additionally, developing context-specific models that reflect local socio-economic conditions and involving diverse stakeholders in model development can help minimize bias (Brown *et al*., 2016; Notenbaert *et al*., 2017). However, these practices are not yet universally adopted in emerging markets due to limited technical capacities and weak regulatory mandates.

Transparency and explainability present additional challenges for AI-driven credit scoring systems. Many AI and machine learning algorithms, particularly those based on deep learning, are often described as "black boxes" because they produce outcomes without easily interpretable reasoning. This lack of transparency can make it difficult for consumers to understand why they were approved or denied credit, leading to frustration and distrust.

In traditional lending, credit decisions are often based on well-understood criteria, such as income levels, collateral, and repayment history, which can be explained to applicants. In contrast, AI-driven credit decisions may be influenced by complex and non-obvious factors derived from alternative data sources, making it difficult to provide clear explanations.

Regulators also face difficulties in monitoring these systems due to the technical complexity of AI models. Without adequate explainability, it becomes challenging for supervisory authorities to ensure that credit scoring models comply with fairness, non-discrimination, and consumer protection standards.

Some financial institutions and fintech firms are experimenting with explainable AI (XAI) techniques, which aim to provide understandable rationales for automated decisions. Tools such as Local Interpretable Model-Agnostic Explanations (LIME) and Shapley Additive Explanations (SHAP) are being deployed to enhance model interpretability. However, these tools require technical expertise and may not fully bridge the gap for consumers with limited digital literacy.

Improving explainability is crucial not only for compliance but also for maintaining borrower trust, particularly in emerging markets where skepticism toward digital financial services may remain high.

Finally, regulatory and legal uncertainty poses a major barrier to the safe and effective deployment of AI-based credit scoring systems in emerging markets. Many countries lack comprehensive frameworks for digital lending, AI ethics, algorithmic accountability, and data protection, creating a fragmented and unpredictable regulatory environment.

In some cases, digital lenders operate in regulatory grey areas, raising concerns about consumer protection and systemic risks. Additionally, the cross-border nature of many fintech platforms complicates regulatory oversight, particularly when data storage and processing occur outside the jurisdiction of the borrower's home country (Arner *et al*., 2016; Brummer and Yadav, 2018).

Emerging economies face the dual challenge of fostering innovation in financial technology while safeguarding consumer rights and maintaining market stability. Regulatory agencies often struggle with limited technical capacity and resources to effectively oversee complex AI models and fintech platforms.

To address these gaps, several countries have introduced regulatory sandboxes, allowing fintech firms to test innovative products under regulatory supervision. However, these sandboxes are often temporary and do not provide long-term regulatory clarity. Broader reforms are needed to establish legal frameworks that balance innovation with accountability, covering areas such as AI transparency, algorithmic fairness, data sharing, cross-border data flows, and consumer recourse mechanisms.

AI-driven credit scoring systems present immense potential for advancing financial inclusion in emerging markets. However, their benefits can only be fully realized if significant risks and challenges are addressed. Key concerns include safeguarding data privacy and security under evolving regulatory frameworks, preventing algorithmic bias that may entrench existing socio-economic disparities, ensuring transparency and explainability to both regulators and borrowers, and resolving regulatory uncertainties that currently undermine responsible deployment.

These challenges require collaborative efforts among fintech companies, financial institutions, regulators, and civil society organizations. By implementing robust data governance practices, developing fair and interpretable AI models, and establishing clear legal frameworks, emerging markets can mitigate risks while leveraging AI-driven credit scoring as a tool for inclusive, equitable, and sustainable financial systems (Veale and Binns, 2017; Vollmer *et al.*, 2018).

2.4 Best Practices and Mitigation Strategies

As AI-driven credit scoring systems become more prominent in emerging markets, ensuring their responsible and ethical use is critical to promoting financial inclusion while safeguarding consumer rights. Without proactive strategies, these systems may exacerbate inequalities, undermine trust, and trigger regulatory backlash. To mitigate the risks associated with bias, privacy, opacity, and regulatory uncertainty, a set of best practices and mitigation strategies has emerged as shown in figure 3(Kumarasiri and Gunasekarage, 2017; Lepri *et al.*, 2017). These include the implementation of ethical AI principles, robust data governance and consumer consent frameworks, AI explainability tools, and collaborative regulatory sandboxes. Together, these practices can foster responsible innovation in digital credit scoring.

A central best practice in deploying AI-driven credit scoring systems is the adherence to ethical AI principles and the institutionalization of fairness audits. AI systems can unintentionally reinforce social and economic biases, leading to discriminatory outcomes in credit decisions. To counteract this, lenders and technology providers must integrate fairness as a core design and operational criterion.

Fairness audits are systematic evaluations of AI models to detect, measure, and mitigate bias. These audits involve analyzing model outcomes across demographic variables such as gender, ethnicity, age, and geographic location. Tools like disparate impact analysis and counterfactual fairness testing help identify whether certain groups face disproportionate disadvantages in credit assessments.

Institutions should adopt AI governance frameworks that incorporate ethical principles such as fairness, accountability, and non-discrimination. Organizations such as the Institute of Electrical and Electronics Engineers (IEEE) and the OECD have developed guidelines to promote trustworthy AI, which can serve as reference points for credit scoring applications.

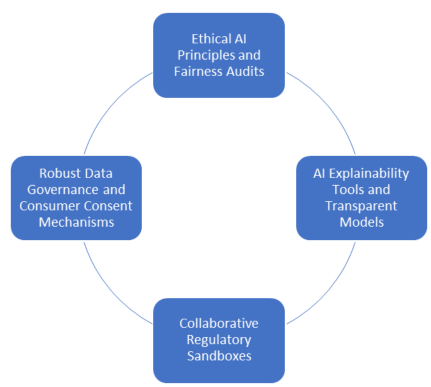

Figure 3: Best Practices and Mitigation Strategies

Moreover, fairness testing should not be limited to pre-deployment phases. Continuous monitoring of models after deployment is essential to ensure that fairness remains consistent as new data are introduced. This practice is particularly important in emerging markets where socio-economic conditions and borrower behaviors can change rapidly.

Given the reliance of AI-driven credit scoring systems on sensitive personal and behavioral data, robust data governance and consumer consent mechanisms are fundamental to safeguarding privacy and ensuring legal compliance (Selbst and Barocas, 2018; Winfield and Jirotka, 2018).

Compliance with comprehensive data protection regulations, such as the General Data Protection Regulation (GDPR) in the European Union, should serve as a benchmark for credit scoring providers. GDPR principles—such as data minimization, purpose limitation, and data subject rights—should be adapted to local contexts in emerging markets, many of which are developing their own data protection frameworks (e.g., Nigeria's Data Protection Act, Kenya's Data Protection Act, and India's Digital Personal Data Protection Act).

An essential aspect of responsible data governance is obtaining meaningful and informed consent from consumers. This involves clearly explaining what data will be collected, how it will be used, and with whom it will be shared. Consent requests must be presented in user-friendly language, avoiding technical jargon that could confuse consumers with limited digital literacy.

Data anonymization, encryption, and secure storage protocols should also be implemented to protect personal information from breaches and unauthorized access. Additionally, organizations should establish clear procedures for data deletion and correction upon user request.

Developing trust in digital credit scoring systems also requires engaging consumers in understanding their data rights and the potential risks of sharing personal information. Financial literacy programs focusing on digital rights and privacy can empower consumers to make informed decisions about participation in AI-based credit services.

Transparency and explainability are vital for both regulatory compliance and consumer trust in AI-driven credit scoring systems. Given the complexity of many machine learning algorithms, especially deep learning models, simplifying credit decisions and making them interpretable is a key mitigation strategy.

One approach involves using explainable AI (XAI) tools to clarify how credit decisions are made. Techniques such as Local Interpretable Model-Agnostic Explanations (LIME), Shapley Additive Explanations (SHAP), and counterfactual explanations can reveal the key factors influencing model predictions (Hall, 2018; Gudovskiy *et al.*, 2018). These tools allow developers, regulators, and end-users to understand why certain applicants receive approval or rejection.

Financial institutions and fintech companies can also adopt simplified credit scoring models, especially for products aimed at low-income or first-time borrowers. While advanced models offer high predictive accuracy, simpler models—such as decision trees or logistic regression—may provide greater transparency and ease of explanation.

Consumer-facing disclosures play a crucial role in demystifying AI-based credit decisions. Lenders should provide borrowers with clear explanations of credit decisions, including the data inputs used and the rationale behind the outcome. Such disclosures enable consumers to identify errors, contest decisions, and make more informed financial choices. Promoting algorithmic transparency also supports regulatory oversight by allowing supervisors to audit credit models and assess their compliance with fairness, non-discrimination, and consumer protection laws.

Collaborative regulatory sandboxes represent another best practice for balancing innovation and oversight in AI-based credit scoring. Sandboxes provide a controlled environment where fintech firms, financial institutions, and regulators can test new credit solutions under defined regulatory parameters and risk mitigation protocols.

Through regulatory sandboxes, innovators can pilot AI credit scoring models with real users while working closely with regulators to address compliance issues such as data protection, algorithmic fairness, and consumer protection. Regulators, in turn, gain firsthand exposure to

emerging technologies, allowing them to develop more informed and adaptive regulatory approaches.
Several emerging markets—including Kenya, Nigeria, India, and Mexico—have launched regulatory sandboxes to facilitate responsible fintech innovation. These sandboxes often include specific provisions for AI and digital lending solutions, reflecting their growing importance in expanding credit access.

Key benefits of sandboxes include early identification of risks, accelerated regulatory approvals, and enhanced collaboration between public and private stakeholders. Additionally, sandboxes promote iterative learning, allowing both regulators and innovators to refine their approaches based on empirical evidence and user feedback (Omarini, 2018; Hendrikse *et al*., 2018).

To maximize impact, sandboxes should adopt clear evaluation criteria that incorporate ethical AI principles, fairness metrics, data governance standards, and consumer impact assessments. Furthermore, insights generated from sandbox projects should be shared with the broader financial ecosystem to foster collective learning and capacity building.

The adoption of AI-driven credit scoring systems in emerging markets offers unprecedented opportunities for financial inclusion, yet it also presents serious challenges related to fairness, privacy, transparency, and regulation. Addressing these risks requires a comprehensive and proactive strategy centered on best practices and mitigation measures.

Embedding ethical AI principles and conducting regular fairness audits can help prevent discriminatory outcomes. Robust data governance frameworks and meaningful consumer consent mechanisms are crucial to protecting personal information and complying with evolving legal standards. AI explainability tools and simplified models enhance both regulatory oversight and consumer trust by making automated credit decisions more transparent and understandable. Collaborative regulatory sandboxes provide a safe space for testing and refining innovative credit solutions under regulatory guidance.

By institutionalizing these practices, emerging markets can foster responsible innovation in AI-based credit scoring, enabling inclusive, ethical, and sustainable financial ecosystems that benefit both underserved populations and the broader economy (Hong *et al*., 2017; Chakravorti, 2018).

2.5 Future Directions and Policy Recommendations

As AI-driven credit scoring systems become increasingly central to financial inclusion strategies in emerging markets, their future development requires careful consideration of ethical, technical, and regulatory dimensions. While these technologies have proven effective in expanding credit access to underserved populations, sustaining their long-term benefits depends on the implementation of forward-looking policies and collaborative action (Celestin and Vanitha, 2016; Mashnik *et al*., 2017). This outlines key future directions and policy recommendations that can guide responsible scaling of AI-based credit scoring systems, focusing on inclusive model development, cross-sector partnerships, investment in digital infrastructure and literacy, and the establishment of global standards for fairness and accountability.

One of the most urgent priorities for the future of AI-driven credit scoring is the development of more inclusive and context-specific models. Many existing credit scoring algorithms are trained on data that do not fully represent the diversity of populations in emerging markets, which can lead to biased outcomes and further marginalization of vulnerable groups such as women, rural dwellers, informal workers, and smallholder farmers.

Inclusive AI model development requires intentional efforts to incorporate diverse data sources that reflect the lived realities of these groups. This involves collecting contextually relevant data, such as mobile money usage patterns, local trade networks, informal savings groups, and community-based lending behaviors. Incorporating such data can improve model accuracy and fairness by aligning risk assessments with socio-economic conditions unique to specific regions or demographic segments.

Additionally, local participation in model design and evaluation is critical. Fintech companies and lenders should actively engage community representatives, civil society organizations, and user groups in the model development process to ensure that AI systems address real-world needs and avoid unintended harms. This participatory approach can also foster greater trust and acceptance among target populations.

Investing in the development of AI tools capable of detecting and mitigating bias throughout the modeling lifecycle is another essential step (Brundage *et al*., 2018; Attaran and Deb, 2018). Algorithmic audits and fairness-enhancing techniques—such as re-sampling, re-weighting, and adversarial debiasing—should be integrated into model workflows to minimize discriminatory effects.
Effective and responsible deployment of AI-driven credit scoring systems requires coordinated collaboration among diverse stakeholders, including fintech startups, traditional banks, telecommunications companies, regulators, and non-governmental organizations.

Fintech firms and mobile network operators often possess rich alternative data, such as mobile payment histories and telecom usage patterns, while banks offer experience in credit risk management and customer relationship frameworks. Regulatory bodies, meanwhile, play a critical role in ensuring compliance with consumer protection and data privacy laws.

Cross-sector partnerships enable the pooling of complementary resources, expertise, and data to build more robust and equitable credit scoring models. For instance, telecom companies can collaborate with financial institutions to offer bundled financial services that use telecom metadata for credit scoring while ensuring privacy safeguards.

Furthermore, partnerships with public sector institutions and donor agencies can facilitate the expansion of digital financial services to rural and marginalized areas through subsidies, grants, and technical assistance programs. Collaborative research initiatives between academia and industry can also advance the development of explainable and fair AI algorithms tailored to emerging market contexts.

To maximize the impact of such partnerships, clear governance structures must be established to define data-sharing agreements, accountability mechanisms, and equitable value distribution among partners. Transparent partnership frameworks help ensure that AI-driven credit scoring systems align with broader financial inclusion and consumer protection goals.

Another essential priority for the future of AI-based credit scoring is increased investment in digital infrastructure and digital literacy. Many emerging economies face significant infrastructure gaps, including poor internet connectivity, limited access to smartphones, and inadequate cybersecurity systems. These constraints limit the reach and reliability of AI-based credit assessment tools.

Governments, development finance institutions, and private investors must prioritize the development of digital infrastructure, such as high-speed broadband networks, cloud computing platforms, and secure data storage facilities, particularly in underserved rural and peri-urban areas. Expanding access to digital identification systems and interoperable payment platforms can also improve data availability for credit scoring.

Simultaneously, enhancing digital literacy among consumers is crucial to fostering informed participation in AI-powered financial services. Educational initiatives should focus on building consumer awareness about data privacy, algorithmic decision-making, credit management, and grievance mechanisms (Bodo *et al*., 2017; Tene and Polonetsky, 2017). This knowledge empowers individuals to exercise their rights, evaluate risks, and make informed financial decisions.

Specialized training programs for financial service providers, regulators, and policymakers are also necessary to build capacity in AI ethics, model evaluation, and data governance. A digitally literate ecosystem is essential for both the responsible development and equitable use of AI-driven credit scoring tools.

Given the rapid growth of AI-based credit scoring systems across borders, there is a growing need for global standards that promote fairness, transparency, and accountability. Currently, regulatory approaches to AI and digital lending vary widely across jurisdictions, resulting in fragmented oversight and inconsistent consumer protections.

International financial organizations, such as the World Bank, International Monetary Fund (IMF), and the Bank for International Settlements (BIS), alongside digital rights advocacy groups and standard-setting bodies, should lead efforts to develop harmonized guidelines for responsible AI credit scoring. These guidelines should incorporate principles of fairness, explainability, privacy, security, human oversight, and non-discrimination.
Global standards can help create a level playing field for fintech companies and financial institutions operating across multiple markets, while also strengthening consumer trust and fostering responsible innovation. Regional collaboration through platforms such as the African Union's Smart Africa initiative or ASEAN digital finance forums can support the localization and operationalization of these international guidelines (Vestenskov *et al*., 2017; Spillan *et al*., 2017).

The future of AI-driven credit scoring in emerging markets holds great promise for advancing financial inclusion, but it also necessitates proactive strategies to ensure fairness, equity, and sustainability. Key priorities include the development of inclusive, context-sensitive AI models, the establishment of cross-sector partnerships that leverage shared expertise and data responsibly, and targeted investments in digital infrastructure and literacy to enable widespread and secure adoption.

Equally important is the establishment of global standards for responsible AI credit scoring, which can foster consistency, fairness, and consumer protection across borders (Liang *et al*., 2018; Latonero, 2018). By integrating these future directions into national and international policy agendas, stakeholders can harness AI's potential to create inclusive and resilient financial ecosystems that benefit underserved communities while upholding human rights and ethical principles.

CONCLUSION

AI-driven credit scoring systems represent a transformative force in emerging markets, offering both promising opportunities and significant risks. A key insight from this analysis is the dual nature of these technologies: on one hand, they enable financial inclusion by expanding credit access to underserved populations such as informal workers, small businesses, and low-income individuals; on the other, they introduce complex risks related to data privacy, algorithmic bias, and opacity. While AI models can leverage alternative data sources and advanced algorithms to improve credit assessments, they may also inadvertently reinforce socio-economic inequalities if deployed without appropriate safeguards.

Given this dual potential, responsible innovation emerges as a strategic imperative. Financial institutions, fintech companies, and regulators must carefully balance the efficiency and scalability benefits of AI-driven credit scoring with the need for fairness, transparency, and consumer protection. Ethical AI practices, robust data governance, model explainability, and regulatory oversight are essential to minimize harm while maximizing inclusion. Moreover, continuous fairness audits, data protection mechanisms, and transparent decision-making processes must be embedded into the lifecycle of these systems to ensure trust and accountability.

To fully harness the benefits of AI credit scoring for sustainable financial inclusion, multi-stakeholder collaboration is crucial. Governments, financial service providers, technology firms, regulators, and civil society organizations must work together to develop inclusive models, strengthen digital infrastructure, enhance consumer digital literacy, and establish clear regulatory frameworks. Joint action is necessary to create equitable and resilient credit ecosystems that empower underserved populations, foster economic development, and uphold human rights. By aligning technological innovation with social responsibility, emerging markets can unlock the transformative potential of AI-driven credit scoring while ensuring long-term financial sustainability and inclusion.

REFERENCES

[1] Akinluwade, K.J., Omole, F.O., Isadare, D.A., Adesina, O.S. and Adetunji, A.R., 2015. Material selection for heat sinks in HPC microchip-based circuitries. *British Journal of Applied Science & Technology*, *7*(1), p.124.

[2] Alhaddad, M.M., 2018. Artificial intelligence in banking industry: a review on fraud detection, credit management, and document processing. *ResearchBerg Review of Science and Technology*, *2*(3), pp.25-46.

[3] Anderson, K., Ryan, B., Sonntag, W., Kavvada, A. and Friedl, L., 2017. Earth observation in service of the 2030 Agenda for Sustainable Development. *Geo-spatial Information Science*, *20*(2), pp.77-96.

[4] Arner, D.W., Barberis, J. and Buckey, R.P., 2016. FinTech, RegTech, and the reconceptualization of financial regulation. *Nw. J. Int'l L. & Bus.*, *37*, p.371.

[5] Arner, D.W., Buckley, R.P. and Zetzsche, D.A., 2018. Fintech for financial inclusion: A framework for digital financial transformation. *UNSW law research paper*, (18-87).

[6] Attaran, M. and Deb, P., 2018. Machine learning: the new'big thing'for competitive advantage. *International Journal of Knowledge Engineering and Data Mining*, *5*(4), pp.277-305.

[7] Attaran, M., Stark, J. and Stotler, D., 2018. Opportunities and challenges for big data analytics in US higher education: A conceptual model for implementation. *Industry and Higher Education*, *32*(3), pp.169-182.

[8] Balaraman, P. and Chandrasekar, S., 2016. E-commerce trends and future analytics tools. *Indian Journal of Science and Technology*, *9*(32), pp.1-9.

[9] Bisht, S.S. and Mishra, V., 2016. ICT-driven financial inclusion initiatives for urban poor in a developing economy: Implications for public policy. *Behaviour & Information Technology*, *35*(10), pp.817-832.

[10] Bodo, B., Helberger, N., Irion, K., Zuiderveen Borgesius, F., Moller, J., van de Velde, B., Bol, N., van Es, B. and de Vreese, C., 2017. Tackling the algorithmic control crisis-the technical, legal, and ethical challenges of research into algorithmic agents. *Yale JL & Tech.*, *19*, p.133.

[11] Brown, I., Martin-Ortega, J., Waylen, K. and Blackstock, K., 2016. Participatory scenario planning for developing innovation in community adaptation responses: three contrasting examples from Latin America. *Regional environmental change*, *16*, pp.1685-1700.

[12] Brummer, C. and Yadav, Y., 2018. Fintech and the innovation trilemma. *Geo. LJ*, *107*, p.235.

[13] Brundage, M., Avin, S., Clark, J., Toner, H., Eckersley, P., Garfinkel, B., Dafoe, A., Scharre, P., Zeitzoff, T., Filar, B. and Anderson, H., 2018. The malicious use of artificial intelligence: Forecasting, prevention, and mitigation. *arXiv preprint arXiv:1802.07228*.

[14] Bughin, J., Hazan, E., Sree Ramaswamy, P., DC, W. and Chu, M., 2017. Artificial intelligence the next digital frontier.

[15] Campen, J.T., 2016. Banks, Communities, and Public Policy1. In *Transforming the US Financial System: An Equitable and Efficient Structure for the 21st Century* (pp. 221-249). Routledge.

[16] Cash, D., 2018. Sustainable finance ratings as the latest symptom of 'rating addiction'. *Journal of Sustainable Finance & Investment*, *8*(3), pp.242-258.

[17] Celestin, M. and Vanitha, N., 2016. Social impact of microfinance: Measuring success beyond economic metrics. *International Journal of Advanced Trends in Engineering and Technology (IJATET)*, *1*(2), pp.119-124.

[18] Chakravorti, S., 2018, June. Start-ups–Founders Cardinal Rules. In *International Conference on Smart Electric Drives and Power System was held on* (Vol. 12, p. 13).

[19] Choi, G. and Park, S., 2017. Digital Single Market and the Global Financial Stability. *KIF working paper*, *2017*(6), pp.1-55.

[20] Dhanabalan, T. and Sathish, A., 2018. Transforming Indian industries through artificial intelligence and robotics in industry 4.0. *International Journal of Mechanical Engineering and Technology*, *9*(10), pp.835-845.

[21] Duderstadt, J.J., 2016. The Future of the Public University in America: Beyond the Crossroads, 2002.

[22] Gomber, P., Kauffman, R.J., Parker, C. and Weber, B.W., 2018. On the fintech revolution: Interpreting the forces of innovation, disruption, and transformation in financial services. *Journal of management information systems*, *35*(1), pp.220-265.

[23] Goyal, A., 2017. Conditions for inclusive innovation with application to telecom and mobile banking. *Innovation and Development*, *7*(2), pp.227-248.

[24] Gozman, D., Liebenau, J. and Mangan, J., 2018. The innovation mechanisms of fintech start-ups: insights from SWIFT's innotribe competition. *Journal of Management Information Systems*, *35*(1), pp.145-179.

[25] Green, B., Prince, D., Busby, J. and Hutchison, D., 2017, November. " How Long is a Piece of String": Defining Key Phases andObserved Challenges within ICS Risk Assessment. In *Proceedings of the 2017 Workshop on Cyber-Physical Systems Security and PrivaCy* (pp. 103-109).

[26] Gudovskiy, D., Hodgkinson, A., Yamaguchi, T., Ishii, Y. and Tsukizawa, S., 2018. Explain to fix: A framework to interpret and correct dnn object detector predictions. *arXiv preprint arXiv:1811.08011*.

[27] Guo, Y., Yin, C., Li, M., Ren, X. and Liu, P., 2018. Mobile e-commerce recommendation system based on multi-source information fusion for sustainable e-business. *Sustainability*, *10*(1), p.147.

[28] Hall, P., 2018. On the art and science of machine learning explanations. *arXiv preprint arXiv:1810.02909*.

[29] Hendrikse, R., Bassens, D. and Van Meeteren, M., 2018. The Appleization of finance: Charting incumbent finance's embrace of FinTech. *Finance and Society*, *4*(2), pp.159-180.

[30] Hong, B., Wei, Z. and Yang, Y., 2017. Computer Science and Education.

[31] Iwasaki, K., 2018. Emergence of Fintech Companies in Southeast Asia—Rising Hopes of a Solution to Financial Issues. *Pacific Business and Industries*, *18*(68), pp.1-32.

[32] Jabłonowska, A., Kuziemski, M., Nowak, A.M., Micklitz, H.W., Pałka, P. and Sartor, G., 2018. Consumer law and artificial intelligence: Challenges to the EU consumer law and policy stemming from the business' use of artificial intelligence-final report of the ARTSY project. *EUI Department of Law Research Paper*, (2018/11).

[33] Kanobe, F., Alexander, P.M. and Bwalya, K.J., 2017. Policies, regulations and procedures and their effects on mobile money systems in Uganda. *The Electronic Journal of Information Systems in Developing Countries*, *83*(1), pp.1-15.

[34] Khosla, R., Sagar, A. and Mathur, A., 2017. Deploying Low-carbon Technologies in Developing Countries: A view from India's buildings sector. *Environmental Policy and Governance*, *27*(2), pp.149-162.

[35] Kumarasiri, J. and Gunasekarage, A., 2017. Risk regulation, community pressure and the use of management accounting in managing climate change risk: Australian evidence. *The British Accounting Review*, *49*(1), pp.25-38.

[36] Latonero, M., 2018. Governing artificial intelligence: Upholding human rights & dignity. *Data & Society*, *38*.

[37] Lepri, B., Staiano, J., Sangokoya, D., Letouzé, E. and Oliver, N., 2017. The tyranny of data? The bright and dark sides of data-driven

decision-making for social good. *Transparent data mining for big and small data*, pp.3-24.

[38] Liang, F., Das, V., Kostyuk, N. and Hussain, M.M., 2018. Constructing a data-driven society: China's social credit system as a state surveillance infrastructure. *Policy & Internet*, *10*(4), pp.415-453.

[39] Lumsden, E., 2018. The future is mobil: financial inclusion and technological innovation in the emerging world. *Stan. JL Bus. & Fin.*, *23*, p.1.

[40] Mashnik, D., Jacobus, H., Barghouth, A., Wang, E.J., Blanchard, J. and Shelby, R., 2017. Increasing productivity through irrigation: Problems and solutions implemented in Africa and Asia. *Sustainable Energy Technologies and Assessments*, *22*, pp.220-227.

[41] Mbuyisa, B. and Leonard, A., 2017. The role of ICT use in SMEs towards poverty reduction: A systematic literature review. *Journal of International Development*, *29*(2), pp.159-197.

[42] Mills, K. and McCarthy, B., 2016. The state of small business lending: Innovation and technology and the implications for regulation. *Harvard Business School Entrepreneurial Management Working Paper*, (17-042), pp.17-042.

[43] Mittelstadt, B.D., Allo, P., Taddeo, M., Wachter, S. and Floridi, L., 2016. The ethics of algorithms: Mapping the debate. *Big Data & Society*, *3*(2), p.2053951716679679.

[44] Mostaan, K. and Ashuri, B., 2017. Challenges and enablers for private sector involvement in delivery of highway public–private partnerships in the United States. *Journal of Management in Engineering*, *33*(3), p.04016047.

[45] Mujeri, M.K. and Azam, S., 2018. Role of Digital Financial Services in Promoting Inclusive Growth in Bangladesh: Challenges and Opportunities. *Institute for Inclusive Finance and Development, Working Paper*, *55*, pp.5-25.

[46] Mustapha, A.Y., Chianumba, E.C., Forkuo, A.Y., Osamika, D. and Komi, L.S., 2018. Systematic Review of Mobile Health (mHealth) Applications for Infectious Disease Surveillance in Developing Countries. *Methodology*, *66*.

[47] Notenbaert, A., Pfeifer, C., Silvestri, S. and Herrero, M., 2017. Targeting, out-scaling and prioritising climate-smart interventions in agricultural systems: Lessons from applying a generic framework to the livestock sector in sub-Saharan Africa. *Agricultural systems*, *151*, pp.153-162.

[48] Obiora, S.C. and Csordás, T., 2017. The case of alternative versus traditional financing: A literature review. *Archives of Business Research*, *5*(9).

[49] Oduola, O.M., Omole, F.O., Akinluwade, K.J. and Adetunji, A.R., 2014. A comparative study of product development process using computer numerical control and rapid prototyping methods. *British Journal of Applied Science & Technology*, *4*(30), p.4291.

[50] Olanrewaju, A.R.K., 2018. *Exploring the Strategies for Accessing Microloans Used by Small and Medium Enterprises*. Walden University.

[51] Olaoye, T., Ajilore, T., Akinluwade, K., Omole, F. and Adetunji, A., 2016. Energy crisis in Nigeria: Need for renewable energy mix. *American journal of electrical and electronic engineering*, *4*(1), pp.1-8.

[52] Omarini, A.E., 2018. Banks and FinTechs: How to develop a digital open banking approach for the bank's future. *International Business Research*, *11*(9), pp.23-36.

[53] Oyedokun Oyewale Chioma Susan Nwaimo, Oluchukwu Modesta Oluoha (2019). Big Data Analytics: Technologies, Applications, and Future Prospects. 2(11), pp 441-438

[54] Peck, J. and Whiteside, H., 2016. Financializing detroit. *Economic Geography*, *92*(3), pp.235-268.

[55] Qi, Y. and Xiao, J., 2018. Fintech: AI powers financial services to improve people's lives. *Communications of the ACM*, *61*(11), pp.65-69.

[56] Raj, P. and Raman, A.C., 2017. *The Internet of Things: Enabling technologies, platforms, and use cases*. Auerbach Publications.

[57] Raso, F.A., Hilligoss, H., Krishnamurthy, V., Bavitz, C. and Kim, L., 2018. Artificial intelligence & human rights: Opportunities & risks. *Berkman Klein Center Research Publication*, (2018-6).

[58] Rathore, A.K., Kar, A.K. and Ilavarasan, P.V., 2017. Social media analytics: Literature review and directions for future research. *Decision Analysis*, *14*(4), pp.229-249.

[59] Riikkinen, M., Saarijärvi, H., Sarlin, P. and Lähteenmäki, I., 2018. Using artificial intelligence to create value in insurance. *International Journal of Bank Marketing*, *36*(6), pp.1145-1168.

[60] Sapovadia, V., 2018. Financial inclusion, digital currency, and mobile technology. In *Handbook of Blockchain, Digital Finance, and Inclusion, Volume 2* (pp. 361-385). Academic Press.

[61] Saravanan, R. and Sujatha, P., 2018, June. A state of art techniques on machine learning algorithms: a perspective of supervised learning approaches in data classification. In *2018 Second international conference on intelligent computing and control systems (ICICCS)* (pp. 945-949). IEEE.

[62] Selbst, A.D. and Barocas, S., 2018. The intuitive appeal of explainable machines. *Fordham L. Rev.*, *87*, p.1085.

[63] SHARMA, A., ADEKUNLE, B.I., OGEAWUCHI, J.C., ABAYOMI, A.A. and ONIFADE, O., 2019. IoT-enabled Predictive Maintenance for Mechanical Systems: Innovations in Real-time Monitoring and Operational Excellence.

[64] Spillan, J.E., King, D.O., Spillan, J.E. and King, D.O., 2017. Current business environment. *Doing business in Ghana: Challenges and Opportunities*, pp.13-66.

[65] Taiwo, J.N. and Falohun, T.O., 2016. SMEs financing and its effects on Nigerian economic growth. *European Journal of Business, Economics and Accountancy*, *4*(4).

[66] Tene, O. and Polonetsky, J., 2017. Taming the Golem: Challenges of ethical algorithmic decision-making. *NCJL & Tech.*, *19*, p.125.

[67] Tzanakou, E.M. ed., 2017. *Supervised and unsupervised pattern recognition: feature extraction and computational intelligence*. CRC press.

[68] Veale, M. and Binns, R., 2017. Fairer machine learning in the real world: Mitigating discrimination without collecting sensitive data. *Big Data & Society*, *4*(2), p.2053951717743530.

[69] Vestenskov, D., Shah, A., Kazmi, A. and Hansen, C.H., 2017, June. Approaching Regional Coherence: Promoting Security Cooperation and Economic Connectivity in South Asia. In *RDDC-NUST GTTN Joint International Seminar: Peace, Growth and Empowerment: Promoting Regional Connectivity*. Royal Danish Defence College.

[70] Vollmer, S., Mateen, B.A., Bohner, G., Király, F.J., Ghani, R., Jonsson, P., Cumbers, S., Jonas, A., McAllister, K.S., Myles, P. and Granger, D., 2018. Machine learning and AI research for patient benefit: 20 critical questions on transparency, replicability, ethics and effectiveness. *arXiv preprint arXiv:1812.10404*.

[71] Vu, K. and Hartley, K., 2018. Promoting smart cities in developing countries: Policy insights from Vietnam. *Telecommunications Policy*, *42*(10), pp.845-859.

[72] Wei, Y., Yildirim, P., Van den Bulte, C. and Dellarocas, C., 2016. Credit scoring with social network data. *Marketing Science*, *35*(2), pp.234-258.

[73] Winfield, A.F. and Jirotka, M., 2018. Ethical governance is essential to building trust in robotics and artificial intelligence systems. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, *376*(2133), p.20180085.

[74] Yeung, K., 2018. Algorithmic regulation: A critical interrogation. *Regulation & governance*, *12*(4), pp.505-523.

[75] Zamore, S., Ohene Djan, K., Alon, I. and Hobdari, B., 2018. Credit risk research: Review and agenda. *Emerging Markets Finance and Trade*, *54*(4), pp.811-835.