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AI for Promoting Financial Inclusion

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Abstract:

The new and transformative wave of artificial Intelligence (AI) is no longer news to many, as it is rapidly changing every human sector, and the financial environment is not excluded. Its transformative superpower offers opportunities to address financial inclusion. Based on a rapid literature review, this study examines the role that AI technologies play in bridging the gap between traditional financial ecosystems and financially excluded populations in countries around the world, as well as in developing countries. Using the opportunities presented by natural language processing (NLP), machine learning, predictive analytics, and data analytics, these AI technologies can assist financial institutions to develop a customised financial product, credit scoring process, and system, real-time risk assessment, and assessment for people with limited (little) or no credit history. In addition, AI-driven mobile banking apps, platforms, and chatbots help improve financial knowledge, literacy, skills, and accessibility for those in rural and low-income communities. The potential of AI technologies to promote financial inclusion is quite large and is increasing. However, some challenges include ethical concerns, algorithm bias, data privacy, and a lack of a regulatory framework and process. This chapter sets a conceptual framework for considerations to be made with a view to promoting an ethical and responsible use of AI technologies towards financial inclusion. The model set is built on AI innovation and critical considerations towards promoting financial inclusion, as well as driving economic development, empowerment, and digital finance.

Keywords:

Artificial Intelligence (AI), AI Technologies, Natural Language Processing (NLP), Machine Learning, Financial Inclusion

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Introduction

For decades, the privileged have largely dominated financial systems, while excluding the classes and sectors that are traditionally underserved and underdeveloped. As a reaction to this economic exclusion, financial inclusion must be considered as part of an effort to achieve economic development and growth (Robert, Elly & Elly, 2025). Financial inclusion can contribute to economic development and growth for everyone, even small and medium enterprises (SMEs) (Rasheed et al. 2019), and artificial intelligence (AI) has continued to redefine the financial ecosystem. The world is coming full circle to witness the true and revolutionary prospects of AI in shaping and reshaping financial ecosystems, as well as to enhance access to financial inclusion. Perspectives, even if debatable, suggest that AI can provide an incredibly important window of opportunity to expand financial inclusion by re-arranging traditional financial boundaries rather than expelling underserved/underdeveloped populations and groups from the financial eco-systems in developing nations. As Omogbeme et al. (2024) and Sam-Bulya et al. (2023) suggest, AI technology that involves natural language processing (NLP), machine learning (ML), and predictive analysis has the capabilities that will affect formal financial services, which exclude some due to inaccessibility, unaffordability, and even usability. Researchers have conducted investigations into isolated applications of AI methods to determine the extent of their effect on the unequal problem of access to finance and any type of exclusion that leads to being underserved.

Through AI, it is possible to assess creditworthiness without a credit history, through mobile phone data and other transaction history, to generate a credit score (Addy et al., 2024; Faheem, 2021; Sam-Bulya et al., 2023; Nwaimo, Adegbola & Adegbola, 2025). It should be noted that AI technologies drive cost-effective (low-cost) access to banking history information that facilitates loan evaluation and approval using an automated credit assessment mechanism and customised financial services (Zou, 2025).

However, the process of automating financial evaluation and access is challenged by vulnerabilities such as fraud, hacking, scamming, and others. However, research suggests that AI technologies play a critical role in mitigating these threats. These threats can be mitigated according to Sam-Bulya et al. (2023) those who believe that AI technologies make it easy to assist in mitigating threats, such as risk management, fraud detection, and improved customer experience by supporting multilingual. Notwithstanding the positive promises of AI-driven technologies, implementation is further challenged by different issues such as privacy concerns, the digital divide, and the regulatory framework (Yasir et al., 2022; Zou, 2025). Also, notwithstanding the level of attention on financial inclusion, millions and even billions of underserved populations are left outside the traditional financial ecosystem (Robert, Elly & Elly, 2025). Then, this study aims to explore the role of AI technologies, such as natural language processing, machine learning, predictive analytics, and data analytics, in promoting financial inclusion among excluded populations worldwide.

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Problem Statement

Financial inclusion into the financial mainstream remains a challenge for undeserved or excluded populations (Robert, Elly & Elly, 2025). Continuous development in technology, such as AI, provides the opportunity for traditional financial industries and institutions to expand their customer base by simplifying access to financial services. The changes and transformations of AI tools bridge the financial divide and other financial exclusions. Nevertheless, the potential of the AI financial sector, around 1.7 billion adults worldwide are unbanked as a result of accessibility, availability, and financial product affordability, which exclude these groups such as small-scale entrepreneurs, women, and rural populations (Omogbeme, Phil-Ugochukwu, Nwabufo & Onyebuchi, 2024). Academics are beginning to pay attention to investigating how AI technologies can be used to promote financial inclusion. For example, scholars such as Omogbeme et al. (2024) and Adeoye et al. (2024) believe that AI technologies such as predictive analytics, NLP, and machine learning help promote financial inclusion among underdeveloped and marginalised populations. These technologies assist financial institutions in accessing different databases and datasets to determine clients' risk level through the assessment of individual creditworthiness (Adeoye et al., 2024). In addition, scholars believe that AI technologies provide solutions to conventional banking issues, such as lack of access to credit, financial literacy, fraud detection, high-cost infrastructure, and the ability to provide customised banking services, virtual assistance, and chatbots (Akanfe, 2025; Adeoye et al., 2024; Oyedokun et al., 2025). Academics have examined how these AI methods can address financial access challenges and financial requirements that prevent underserved populations from accessing banking services.

Adeoye et al. (2024), for example, documented how data analytics assist financial institutions in creating alternative models of credit scoring behavior, using mobile phone or smartphone data to access those with no conventional credit scores. These technologies have allowed underprivileged and excluded populations to access bank savings, microcredit, and insurance in developing countries in Asia and Africa (Oyedokun et al., 2025). The researchers further articulated that AI technologies simplified the opening of new bank accounts, created smart and personalised financial products, improved efficiency and risk detection, as well as management for the unbanked (Ozili, 2023 #526). Nevertheless, the transformation of AI technologies to break the financial divide faces some challenges. According to Yasir et al. (2022) and Oyedokun et al. (2025), the challenges include privacy issues and concerns, algorithm bias, and eliminating the digital divide, which must be achieved by formulating regulatory mechanisms and frameworks. Other researchers also acknowledged that financial institutions face ethical challenges, privacy and security concerns, and the digital divide while trying to implement AI technologies for financial inclusion (Zou, 2025). While Ozili (2023) suggests that implementation of AI for financial inclusion is confronted by a shortage of AI-skilled workers, system bias, increased unemployment at the financial institution, and barriers from data privacy laws.

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Based on these positive and negative perspectives on the implementation of AI technologies for financial inclusion. Then, this study examines the role of AI technologies, such as natural language processing, machine learning, predictive analytics, and data analytics, in promoting financial inclusion among excluded populations around the world. Finally, the study proposes a dynamic AI-Driven Financial Inclusion Framework (AI-DFIF) that assists in the process of applying AI technologies in promoting financial inclusion, especially for developing countries.

Research Objectives

1. Explore how AI technologies can promote financial inclusion.
2. Evaluate the impacts of AI technologies in providing easily accessible, affordable, and personalised financial services in promoting financial inclusion.
3. Identify the challenges and limitations facing the adoption of AI technologies in the promotion of financial inclusion.

Research Methods

Recently, the potential and possibilities of AI technologies in transforming the financial landscape to promote financial inclusion are drawing the attention of government, industry, and academics. Scholars continue to research the application and roles of AI technologies in addressing social equality, such as financial inclusion, using different research methodologies. In general, information systems research adopts different research methods, such as qualitative, quantitative, mixed methods, and even secondary data, when conducting research. Rapid literature reviews (RLRs) form part of the qualitative research method under the literature review method. According to Garritty (2021), Tricco et al. (2015), and Ganann (2010), RLRs are a research method used to synthesize reviews of the academic literature to produce evidence for decision-making in a short period of three (3) weeks to twelve (12) months. This methodology is widely used in policy making and health research, but there is no common or standard definition (Smela, 2023). According to Haby et al. (2016), this methodology lacks a standardised process that guides its application.

Furthermore, RLRs are criticised for database-limited searches, defined by inclusion criteria by language and date, excluding quality assessments and screening, and data extraction (Tricco et al., 2015). The researchers further suggested that the findings of the RLRs may be biased, which can lead to the exclusion of relevant information. Although reporting can be of poor quality and lacking a standardised methodology and approaches (Ganann, 2010; Tricco et al., 2015). However, Martin et al. (2020) observed that RLRs are well-suited for healthcare research because of their rigour and quick timeline. Can it be applied in information systems (IS) research? The answer is yes because it assists IS researchers in researching emerging topics and quickly contributes to the decision-making process.

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The RLRs are deployed promptly in this study, looking at the role of AI technologies, such as natural language processing, machine learning, predictive analytics, and data analytics, in promoting financial inclusion among excluded populations around the world. It involves inclusion and exclusion criteria. The inclusion and exclusion criteria are used to ensure that the scope is defined, rigour and transparency are maintained, and reproducibility can be ensured.

The inclusion criteria:

- **Timeframe:** The publications to be considered are within a period defined for relevance. For example, publications within 5 to 10 years.
- **Population:** Studies that focus on a particular area or group of the study.
- **Language:** The English language papers were used in the study, which may introduce some form of bias and a limited literature search.

The exclusion criteria:

- Studies not within the defined population.
- Studies outside the defined timeframe.
- Publications written in any language other than English.
- Non-empirical research and sources.

Results and Findings

The findings of this chapter focus on the research objectives listed above. However, the section began with an in-depth overview of financial inclusion, after which the research objectives were discussed comprehensively.

Financial Inclusion

The development of technology in the 21st century promises many changes, advancements, economic growth, and empowerment, especially in the financial sector. Over the years, traditional financial ecosystems have failed to provide inclusive products and services to all populations. These inabilities widen financial exclusion as a result of a number of issues that propel the call for an appropriate system and approach to promote financial inclusion for underserved populations. According to Nwaimo, Adegbola, and Adegbola (2025), the current assessment of financial services, such as credit scoring, fails to provide an accurate and inclusive financial assessment of creditworthiness in relation to marginalised populations.

Financial inclusion is the ability to include those excluded from the traditional financial ecosystem. According to Sarma and Pais (2011), financial inclusion is a process that provides equitable and timely access to financial services. Sarma (2008) further regards financial inclusion as the ability for all

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members of the public or the economy to have easy access, availability, and usage of financial services. This growth is facilitated by emerging technologies, such as AI tools, to extend invited groups and communities to the formal financial system (Akanfe et al., 2025). It enables expansion of equal opportunity to all in order to achieve access and availability of financial products and services (Bello, 2024). The services include credit access and other loan products oriented. Financial inclusion, based on this research, is addressing equitable access, availability, and usability of financial services for all people in society. This involves non-discrimination and easy access, and is useful to financial services for all. Equal access covers the poor, young people, women, and persons with disabilities to engage in traditional financial services (Demirgüç-Kunt & Klapper, 2012). Inclusion gears towards protecting the poor and marginalised from the financial ecosystem (Subbarao, 2009).

The Use of Artificial Intelligence (AI) Technologies to Promote Financial Inclusion

Studies indicate that AI technologies are used to address the commonly known barriers that confront financial inclusion in developed and developing countries. Financial inclusions are directed towards providing accessible, available and affordable financial services for all in eliminating poverty and increasing economic empowerment (Omogbeme, Phil-Ugochukwu, Nwabufo & Onyebuchi, 2024). In practice, AI assists financial institutions in accessing underdeveloped and underserved communities and providing them with alternative financial services such as credit scores using social media events and other means, bypassing credit history requirements (Omokhoa et al. 2025; Sam-Bulya et al. 2023). The following AI technologies were discussed to highlight their role in promoting financial inclusion.

Natural Language Processing (NLP)

NLP is a subdivision of AI with the ability to analyse and understand human text and language (Lan, Mohammed, Elly & Happiness, 2025). The role of NLP is transformative in nature by opening new aspects for data-oriented decision making (Du, Zhao, Mao, Xing & Cambria, 2024). The role of NLP in financial institutions is gaining academic attention, more specifically in promoting financial inclusion and combating different financial fraud incidents. Financial fraud remains a challenging task for financial institutions in this global economic system. Based on the nature of financial fraud or criminality, the ability of financial institutions to detect and prevent this fraud is a challenge. According to Lan, Mohammed, Elly and Happiness (2025), NLP can be used as a tool to detect and prevent financial fraud by analysing anomalous textual data, language patterns, and other inconsistencies. At this point, underprivileged, unemployed, and underserved populations are being neglected and sidelined when it comes to access to financial services for many reasons. NLP can analyse views, opinions, and extract important financial data, automate risk alerts, and trading signals to support and promote decision-making (Osterrieder,

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2023). This ability of NLP means that the social and economic divide against underserved populations can be mitigated by giving them improved access to different financial services and products.

Using NLP, financial institutions can improve the experience and interaction of customers, automate operations and processes, and improve the decision-making process (Favour et al, 2025). It facilitates speed and responds accurately to customer chat and inquiries. According to Favour et al. (2025), big data can be analysed using NLP by scrutinising unstructured individual financial data such as social media posts, market trends, and financial fraud and risks to enhance decision-making.

Machine Learning

Machine learning (ML) is promising as a transformative force in tackling financial inclusion by providing alternative means for fraud detection, credit scoring, risk management, and customized financial products (Robert, Ell & Elly, 2025; Balcıoğlu, 2024). ML models can analyse large financial datasets that include utility bill payments, transaction histories, and customer behaviour (Robert, Elly & Elly, 2025). Based on the potentials and abilities of ML in addressing financial inclusion by segmenting customers and identifying their financial behavioural patterns. According to Robert, Elly and Elly (2025), ML can assist financial institutions to make investment decisions, detect financial anomalies, manage portfolios, and make market predictions. However, it is commonly known that the major challenge for underserved populations in accessing financial systems is a lack of a conventional credit history, but ML provides an alternative to data sources for evaluation. Alternatives can be through social media activities, the use of smartphones (phones), and events of electronic commerce (e-commerce). These datasets provide insightful information to determine customers' creditworthiness (Robert, Elly & Elly, 2025; Sgro, Smalley & Welch, 2019).

In practice, companies like Tala use alternative credit scoring measures to evaluate creditworthiness using customers' social media data, mobile or smartphone usage, and transaction histories (Berg, Burg, Gombović & Puri, 2020; Robert, Elly & Elly, 2025). ML algorithms are used by microfinance organisations to scan customers' risk profiles in order to optimise loans and assist entrepreneurs to access loans (Fuster, Goldsmith-Pinkham, Ramadorai & Walther, 2022; Robert, Elly & Elly, 2025). Then, Community banks and credit unions apply AI-driven chatbots in providing digital and financial literacy and advisory services, and customer experience for unprivileged individuals with customised products (Robert, Elly & Elly, 2025). However, the application of ML to promote financial inclusion is confronted with challenges like data availability and quality, lack of financial records or histories, lack of a regulatory framework, uncertainty, ethical standards, consumer rights, and data protection (Robert, Elly & Elly, 2025). However, the application of ML to promote financial inclusion will help to provide accurate credit risk assessments, leading to actual loan lending (Kumar & Garg, 2018). These positive aspects of ML present the critical role of ML in promoting financial inclusion.

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Predictive Analytics

Predictive analytics provides statistical and analytic techniques for prediction. According to Kumar and Garg (2018) and Olagoke (2025), advanced analytics use machine learning, statistical techniques, and data mining to analyse historical events (activities) and current data, in order to create a predictive model for future event predictions. Using the techniques of statistics, machine learning, data mining, and artificial intelligence, future events can be predicted. In promoting financial inclusion, financial institutions can be proactive in analysing trends and behavioural data to drive decisions. There are various steps in the predictive analytics process. The steps, according to Kumar and Garg (2018), are as follows:

1. **Requirement collection –** to apply a predictive analytic model, the aim of the prediction must be determined and understood. The information and knowledge necessary to gather must be clearly defined. For example, a financial institution that wants to predict customers' risk level, the nature of data like customers' behavioural trends, phone usage, and others to use for the prediction must be defined and identified.
2. **Data collection –** after defining and identifying the customer's organisational data, the nature of the data to collect will also be defined. The data collection involves the combination of data from various data sources, including structured or unstructured data, which are to be verified by the analyst.
3. **Data analysis –** to prepare a predictive model, data is collected and analyzed. Unstructured data is converted into structured data, and its quality is tested. This process allows the analyst to evaluate and eliminate any erroneous and missing data and values. The quality of the predictive model depends on the quality of the data, which means that the conversion must be placed in an acceptable format for the analyst to use.
4. **Statistics and ML –** statistics and ML techniques are used in predictive analytics. In statistics techniques, regression analysis and probability theory are commonly used, while decision trees, artificial neural networks, and support vector machines are considered in ML to apply predictive analytics to provide financial decision-making. These techniques can assist in financial inclusion decisions.
5. **Predictive modeling –** at this stage, a modelling is developed using ML and statistical techniques, as well as available datasets. At the end of the development, the model is tested on the collected datasets and validated, and it will be considered fit for purpose when it is successful.
6. **Prediction and monitoring –** after successful prediction testing, the model can now be used for prediction and decision-making processes. The model generates reports and results that are systematically monitored for correctness and precise predictions.

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As widely used in financial institutions, predictive analytics is used in the sector to enhance operations, facilitate effective resource allocation, and manage risk (Ojika et al., 2023; Olagoke, 2025). Many years of applying predictive analytics in finance have greatly contributed to the fact that data can be collected, analysed, and reported on big data quickly and accurately (Olagoke, 2025). Practically, this helps to assess and achieve a deeper understanding of the risk level of the underserved population by opening access to financial services. For example, previously, credit risk assessments were calculated using debt-to-income and income ratios, which give an aspect of understanding the creditworthiness of the borrower. Today, predictive analytics eliminates these challenges by relying on robust data and computerised techniques that simplify the process by providing credit scores using an ML model in combination with data sources such as economic status (conditions), social media, and spending patterns to produce an accurate assessment (Olagoke, 2025; de Oliveira et al. 2025).).

Data Analytics

Various tools and techniques are used to gain an in-depth understanding of the meaning and interpretation of data for decision-making, and data analytics is one of them. Data analytics is another AI technology used to promote financial inclusion. Data analytics deals with the process of evaluating data, cleaning, altering, and modelling it to extract meaningful insight for decision-making (Bello, 2024; Alem, 2020). To extract actionable insight, meaning, and a deeper understanding from the data to an informed decision, data analytics provides that advanced tool or approach. Data analytics provides techniques to extract and deepen insight from data, driving informed decisions in promoting financial inclusion, particularly in developing nations. Ratnawati (2020) and Osuma (2025) believe that access to affordable and inclusive financial services and products for businesses and individuals is critical in advancing economic prosperity and reducing poverty. The application of data analytics is essential in driving financial inclusion because it drives insight through data, with the ability to identify economically disadvantaged populations, improve credit scoring assessment mechanisms, provide customised financial products and services, as well as improve financial education (literacy) and payment (Bello, 2024; Walker & Paulson, 2025). Data analytics applications to promote financial inclusion are practical in identifying:

Financially excluded, underbanked, and unbanked populations: It involves detecting and profiling populations through the geographic, demographic, and behavioral data of people who are classified as unbanked and underbanked, and providing targeted solutions for them.

Simplifying credit scoring and risk evaluation process: Rather than having to rely solely on conventional financial reporting to provide a consumer with a credit score and risk assessment, alternative scoring methods may exist for consumers who do not have a conventional credit (Óskarsdóttir et al., 2020).

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Customised financial products and services: The use of processes in data analytics to deliver customised financial products and services to a distinct group of individuals is what this entails. Using data analytics, financial institutions can understand the desires and consumption behaviour of individuals and thus offer customised solutions towards financial inclusion (Adedoyin et al., 2025; Del Sarto & Ozili, 2025; Sam-Abugu et al., 2025).

Advancing financial education (literacy): It offers evidence-based financial education and literacy courses and can track its effect on people. According to Abiodun et al. (2021), data analytics assist in identifying gaps in financial literacy, which assist in providing a customised and strategic education programme to promote financial inclusion (Zaimovic et al., 2025).

Accelerating transactions and payments: increases mobile payments and transactions in real-time using data. According to Aguilar et al. (2024) and Morris (2023), through data analytics, digital payments are accelerated, providing a safer, cheaper, and faster experience, which opens access to finance.

Many in developing countries are financially excluded from traditional financial products and services. Through data analytics techniques, financial sectors and organisations (institutions) and policy makers are empowered with the ability to find populations that are not bankrupt and underbanked using different data collection approaches such as surveys and census data with demographic information, comprising their financial histories and services, geographical locations, address, and income levels (Bello, 2024). Data analytics also helps identify their gender, age, education levels, types of occupation, and population groups (race). Bello (2024) and Wang et al. (2023) suggested that mobile data (smartphone), such as usage and call histories, can help with insightful information to showcase financial activities and behaviours.

Importantly, social networks and other online activities provide access to insightful content on individual preferences, transaction activities (trends), social connections, needs and interests, and purchasing behaviours (Bello 2024; Njuguna & Sowon, 2021). When unbanked and underbanked individuals (populations) are known, then data analytics can assist in profiling these individuals according to their personalities, and demographically segment them using factors like gender, age, occupation, education level, and income level to customise financial products and services to groups (Akintola, 2024; Bello, 2024). The current financial products and services of financial institutions can be categorised as one-size-fits-all. But these segmentations empower financial service and product providers to focus on underserved and marginalised populations to provide personalised solutions for their needs, preferences, and expectations. According to Bello (2024), Omotayo et al. (2023), and Almanaseer et al. (2024), mobile (smartphone) usage patterns and financial behaviours assist financial institutions in understanding and identifying individual expectations to design personalised solutions. Additionally, some risk assessment factors, such as employment status, credit histories, and repayment capacity, are

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used by financial institutions to accurately assess the credit history of individuals and provide a risk management process (Mahbobi et al., 2023; Bello, 2024; Șerbu et al., 2021).

Furthermore, data analytics are used by financial institutions to advance individual credit scoring and risk assessment through alternative data, such as utility bills, such as water, electricity, and rent (Bello, 2024). This information helps financial institutions to gain insight into one's payment behaviours and financial abilities. Financial institutions use psychometric tests to assess the psychological and behavioural data of individuals. For example, individual psychological and behavioural data can be tested using a psychometric testing tool to analyse financial risk tolerance, preference, and attitude (Bello, 2024; Roszkowski et al., 2025; Xing, 2024). In addition, data analytics allows financial industry players to deploy models such as (Bello 2024): 1) Predictive models to test one's creditworthiness using ML algorithms such as decision trees, logistic regression, and random forests to scrutinise financial histories to determine one's ability to repay a loan or credit. 2) Behaviour scoring models can evaluate usage patterns and financial behaviour of individuals to determine their creditworthiness and the level of risk profile. 3) Credit scoring models can combine resources from conventional (traditional) and alternative data to assess one's creditworthiness to determine whether one can repay or default on a loan or credit.

By applying data analytics, financial institutions can access individual financial spending, habits, goals, and sources of income to predict their ability to repay on a loan or credit and also assist them in providing customised financial products and services to serve their interest and preferences (Bello, 2024; Broby, 2022). Additionally, data analytics enables financial institutions to provide customised financial education and financial literacy, as well as build optimised mobile banking and payment platforms that target individual needs and preferences (Awan et al., 2021; Bello, 2024). These financial products and services are, so to speak, data-driven products that are based on analyzed data through individual factors and characteristics.

The Impacts of AI Technologies

The influence and effect of AI technologies on advancing financial inclusion are evident through improved access to finance, affordability, and personalised financial products and services to marginalised and underserved populations. AI technologies, as noted by Omogbeme et al. (2024), such as NLP, ML, data analytics, and predictive analytics, are fundamental vehicles for increasing financial access and financial literacy for the public. This component of the study exemplifies a practical aspect of AI technologies, as discussed above, in advancing financial inclusion.

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Easily Accessible

The underserved populations are those who do not receive any incorporation into the traditional financial system and, therefore, have barriers to entry into financial products and services. However, AI technologies are simplifying the access pathway by providing a more simplified access through the gate to financial products and services, particularly to those previously excluded. A great example is China's use of AI technologies to aid financial institutions in providing low-cost loans and access to lending for the unbanked and underbanked population, aided by AI metrics to evaluate and position financial products and services to personalise to their needs (Zou, 2025). This accessible approach to financial services can only happen through the use of AI tools to identify and manage potential risk, eliminate irregularity (information asymmetry), implement chatbots to offer customer support, and implement smarter fraud and risk detection and cybersecurity (Mhlanga, 2020).

In practice, big analytics assists in market segmentation and offers cost-effective and personalised financial products and services (Kshetri, 2021). AI technologies analyse consumer financial transactions and activities, and hopefully allow financial institutions to assist underserved, unbanked, and underbanked groups using customer economic models to serve their interests and needs. Access to financial products and services requires competitive market conditions, regulatory conditions, infrastructure investment, fixing vulnerabilities, and advanced fraud detection systems to enable the financial inclusion of underserved consumers in the financial ecosystem (Biallas & O'Neill, 2020; Yasir et al., 2022).

Affordable

For the unbanked and underbanked, affordability is still a sustained challenge for these populations. AI technologies are shifting the financial landscape by providing affordable financial products and services to millions and billions. Zou (2025) reports that low-cost financial products and services can be delivered through AI-driven financial solutions to promote and achieve financial access and financial inclusion. Oyedokun et al. (2025) report that FinTech companies have created opportunities for millions of people in Asia and Africa to gain access to affordable microfinancial services such as savings products, insurance, and microcredits.

However, the digital divide, algorithm biases, lack of formal regulatory frameworks, ethical guidelines, and privacy concerns continue to challenge AI technologies (Oyedokun et al., 2025; Zou et al., 2025) in providing affordable financial products and services for underserved populations. However, according to Kapoor et al. (2018), personal data protection should be put in place to ensure appropriate protection.

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Personalised Financial Services

The power of AI technologies is to advance personalised financial products and services based on collected and analysed data. Currently, financial institutions are using AI technologies to collect and analyse data and offer customised services based on customer experiences and other factors to promote financial inclusion (Vandanapu, 2024). These financial products and services make it easy for the unbanked and underbanked to join the formal financial system. According to Gupta et al. (2024) and Bhuiyan (2024), AI technologies such as ML, NLP, and data analytics advance customer risk assessment, experience, and automate financial decisions. The researchers further alleged that customised financial solutions such as credit scoring models, robot-advisors, and fraud detection systems increase financial accessibility.

Then, according to Jejeniwa et al. (2024), the promising potential of AI technologies in the tailoring of financial products and services improves credit scoring, fraud detection, and risk management. In return, the personalization of financial products and services increases quality access to the financial system.

The Challenges and Limitations Confronting the Adoption of AI Technologies

The adoption of AI technologies to promote financial inclusion is challenged on multiple fronts, from ethical considerations to technical, regulatory, and organisational. Especially, African and other emerging continents are heavily challenged in the adoption of AI technologies to promote financial inclusion. However, AI technologies present a powerful force in confronting financial exclusion using their tools and techniques. Similarly, research has shown that AI technologies are well-suited to promote financial inclusion. According to Mhlanga (2020), AI technologies advance financial inclusion digitally by improving risk detection and its management, tackling information irregularities (asymmetry), using chatbots to provide customer-centric support, and detecting fraud and cybersecurity. However, there are some obstacles affecting the adoption of AI technologies in facilitating financial inclusion. According to Ozili (2023), the challenges can be AI algorithm biases, a lack of skilled workers, restrictions on privacy laws, and unemployment in the financial sector. There are challenges for Africa, such as data quality issues, lack of infrastructure, and ambiguous regulation (Lottus et al., 2023). Some of the challenges can be the lack of data availability, digital infrastructure in many economies of Africa (Mdladla et al., 2024), and accessibility problems (Jejeniwa et al., 2024).

The current shift is in customer-centric service models, but the challenge is in algorithm transparency, data governance, and ethical implications (Mogaji et al., 2022; Jafar et al., 2023). Nevertheless, a successful adoption of AI facilitates regulatory frameworks and appropriate infrastructure, but government agencies and financial institutions need to increase AI adoption (Yasir et al., 2023) to increase financial inclusion for vulnerable communities and populations.

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Theoretical Contributions

This conceptual framework illustrates the role of AI technologies in promoting financial inclusion to bring underserved and marginalised communities and populations into financial ecosystems. The framework is divided into four parts: AI technologies' core inputs, processes (applications), financial inclusion results, and moderating and challenging factors.

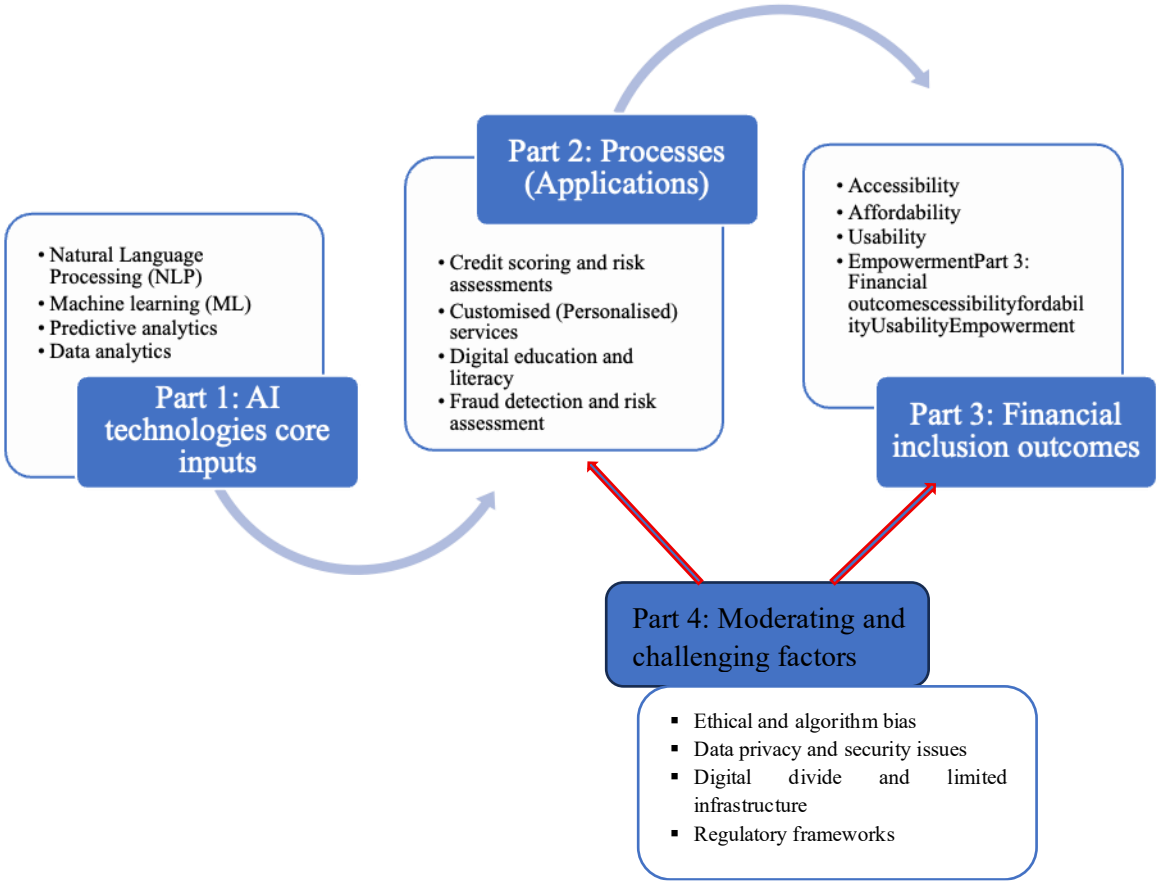

Figure 1: AI-Driven Financial Inclusion Framework (AI-DFIF)

Part 1: Core Inputs of AI Technologies

The first part of the conceptual framework presents the core AI technologies tools that have the capacity to change financial ecosystems, with the ability to receive and process data. Each of the AI technologies transforms data inputs for decision-making. For example:

- **Natural Language Processing (NLP):** advances customer experiences and interactions, fraud detection, supports multilingual services, and automated customer services using chatbots and robot-advisors (Lan et al., 2025; Osterrieder, 2023).

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- **Machine Learning (ML):** It uses alternative credit scoring from non-conventional or traditional data (for example, social media activities, mobile or smartphone usage, and utility bills), supports the detection of fraud, and makes market predictions (Berg et al., 2020; Robert, Elly & Elly, 2025).
- **Predictive analytics:** Customer risk can be forecast, financial behaviours identified, and creditworthiness determined using ML techniques and statistical methods to provide an informed decision-making process (Kumar & Garg, 2018; Olagoke, 2025).
- **Data analytics:** obtains actionable and real-time insights of customer behaviours, demographics, and financial datasets to determine the creditworthiness of excluded and marginalised populations (Bello, 2024; Óskarsdóttir et al., 2020). This determination customises financial services and products in the acceleration of digital payment and transactions

Part 2: Processes (Applications)

This part is the mechanisms and applications that AI technologies work towards enabling financial equality and accessibility.

- **Credit scoring and risk assessments:** AI technologies advance risk assessments and profiling using alternative data sources to eliminate the challenges of unbanked, underserved, and underbanked populations.
- **Customised (Personalised) services:** AI technologies can provide tailored products and services, insurance, loans, and advice aimed at meeting a particular need and expectation.
- **Digital education and literacy:** AI technologies provide real-time and instant financial awareness, education, and literacy suitable for underserved populations.
- **Fraud detection and risk assessment:** AI technologies enable advanced cybersecurity, anomaly monitoring, and provide secure digital transactions.

Part 3: Financial Inclusion Outcomes

These are the intended results of the application of AI technologies to underserved, marginalised, unbanked, and underbanked populations.

- **Accessibility:** Access to financial products and services is extended to unbanked, underbanked, marginalised, and rural communities without barriers.
- **Affordability:** AI technologies decrease financial operational costs, provide digital and mobile banking opportunities, low-cost microfinance, and insurance.

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- **Usability:** AI technologies make it easy to use digital systems in a simplified manner and, in return, advance and influence adoption for underbanked, unbanked and marginalised populations.
- **Empowerment:** An increase in digital education and literacy empowers citizens to engage in secure payment and transactions, also enabling them to trust in the financial ecosystem, which drives socio-economic development and empowerment.

Part 4: Moderating and Challenge Factors

These are external factors that influence how AI technologies can shape and effectively drive sustainable and informed financial inclusion. These factors must be considered in the adoption of AI technologies for financial inclusion.

- **Ethical and algorithm bias:** Unintentionally, AI technologies can increase social and economic inequalities when the trained data is incomplete or biased. For example, in credit scoring, women, youth, and underserved populations without a digital financial history or footprint can be disadvantaged. This directly promotes financial exclusion rather than inclusion.
- **Data privacy and security issues:** Data is the oil of AI technologies; however, securing this data is a challenge for financial institutions. So, personal financial data must be protected. The protection measures of these data make it difficult for identity theft, surveillance, and misuse of personal data.
- **Digital divide and limited infrastructure:** In developing nations, the digital divide and infrastructure gaps are a great challenge for the adoption of AI technologies and any other technologies. These challenges range from limited or a lack of skilled workers, a lack of digital literacy or education, limited internet connectivity, and many more. The digital divide hinders the full acceleration of financial inclusion for underserved, unbanked, and underbanked populations.
- **Regulatory frameworks:** In the application of AI technologies, there are no clear and structured regulatory policies and frameworks to drive adoption. The lack of this hinders and brings distrust in the adoption process. Unstructured and uncertain regulatory policy and framework make it difficult for financial institutions to implement AI technologies and promote financial inclusion for underbanked, unbanked, and marginalised populations.

Practical Implications

The practical implication of this chapter is multiple-fold for policymakers, financial institutions, and underserved (marginalised) populations.

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- **Financial institutions:** This chapter found that AI technologies provide cost-effective tools to increase their products and services, relying on alternative data sources from mobile or smartphone usage, utility payments, and social media activity to determine customer creditworthiness, manage risk, and reduce operational costs. The finding indicates that financial institutions do not need to depend on formal financial data to make credit decisions on customers.
- **Policymakers:** AI technologies are designed to provide targeted solutions for underserved, underbanked, and unbanked populations, advancing regulatory frameworks towards promoting financial inclusion for all.
- **Underserved (marginalised) populations:** Underserved populations have received customised financial products and services, advanced digital financial education, and literacy. These implications for developing nations will accelerate entrepreneurial interest, economic empowerment, and decrease poverty. However, algorithm bias, data privacy and security, and lack of infrastructure must be addressed and eliminated.

Contributions to Existing Knowledge

This study contributed to the growing body of knowledge on financial inclusion through AI technologies such as ML, NLP, predictive analytics, and data analytics. These technologies improve financial access, reduce affordability, and help provide customised financial products and services for unbanked, underbanked, and marginalised populations. This chapter adds theory by designing a framework that amplifies AI technologies that address financial inclusion. It also contributes to the social balance framework with the ability to socially and economically eliminate traditional challenges and barriers that marginalise some populations in developed and developing countries from participating in the formal financial ecosystem.

Empirically, this chapter was based on a rapid review of the literature, with findings that indicate that financial institutions in Asia and Africa are leveraging AI technologies to improve financial access and provide customised financial education and literacy to promote financial inclusion. Theoretically, the chapter proposed a framework to provide a responsible introduction of AI technologies that focus on ethical principles, regulatory and policy framework, and transparency to guide financial institutions and policymakers in the adoption of sustainable financial inclusion.

Conclusions

It is proven that AI technologies can potentially transform the traditional financial ecosystem and open up inclusion for marginalised populations. To expand financial inclusion, credit scoring is simplified, customised products and services are provided, financial literacy and education are enhanced, and

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digital payment and transactions are accelerated. Importantly, the digital divide between marginalised populations and formal financial sectors and players is bridged through the power of AI technologies. The chapter can conclude by noting that AI is not a silver bullet with magic power, but its success in addressing financial inclusion depends on intentionally addressing and tackling existing ethical concerns, algorithm bias, privacy and security risk concerns, and regulatory issues. A comprehensive and well-thought-out framework that is built on inclusivity, innovation, and regulatory governance is critical to achieving a successful and sustainable financial inclusion that focuses on the unbanked, marginalised, underbanked, and underserved populations.

The role of AI goes beyond poverty alleviation, economic empowerment, and digital and financial equity for developed and developing nations. Rather, financial institutions and governments across the world should make intentional efforts to implement AI and its techniques to drive financial inclusion. In the future, studies can focus on looking at how other AI techniques, such as explainable AI and federated learning, can be used to promote financial inclusion for unbanked, marginalised, underserved, and underbanked populations. Studies can look at how these AI techniques can tackle ethical, infrastructural, and regulatory challenges in different social, economic, and political contexts.

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