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Financial inclusion and large language models

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Abstract

Large language models have gained popularity, and it is important to understand their applications in the financial inclusion domain. This study identifies the benefits and risks of using large language models (LLMs) in the financial inclusion domain. We show that LLMs can be used to (i) summarize the key themes in financial inclusion communications, (ii) gain insights from the tone of financial inclusion communications, (iii) bring discipline to financial inclusion communications, (iv) improve financial inclusion decision making, and (v) enhance context-sensitive text analysis and evaluation. However, the use of large language models in the financial inclusion domain poses risks relating to biased interpretations of LLM-generated responses, data privacy risk, misinformation and falsehood risks. We emphasize that LLMs can be used safely in the financial inclusion domain to summarise financial inclusion speeches and communication, but they should not be used in situations where finding the truth is important to make decisions that promote financial inclusion.

Keywords: financial inclusion, large language models, LLM, algorithm, risk, benefit, communication, speech, artificial intelligence, digital financial inclusion

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1. Introduction

This study identifies the benefits and risks of using large language models (LLMs) in the financial inclusion domain. Financial inclusion refers to access and use of affordable basic financial services by members of the population (Sarma and Pais, 2011; Ozili, 2025a). Financial inclusion has immense benefits to society. Financial inclusion gives people access to a bank account, mobile money account, insurance, payment and credit products which they can use to start a business, earn income, own an asset, become financially independent and economically empowered (Ozili, 2025b). Policymakers play a fundamental role in increasing the level of financial inclusion in society. They can introduce regulations and policies that increase the demand and supply of formal financial services e.g., banking, credit, payment and insurance products. They can issue banking licenses to microfinance institutions operating in rural communities to serve financially excluded people, and they also issue payment license to Fintech and Bigtech players to broaden and deepen digital financial inclusion (Frost et al, 2021).

A major aspect of any financial inclusion strategy is financial inclusion communication. Policymakers communicate their plans, intentions and the progress they have made in financial inclusion to stakeholders. Financial inclusion communication is aimed at informing the local and international community about their policy stance towards financial inclusion. For example, policymakers often communicate their national financial inclusion strategy for the next 5-10 years. They also communicate their intention to introduce regulations that give customers greater access to a wide variety of low-cost financial services. Such financial inclusion communication, either through official statements or speeches of the authorities responsible for financial inclusion, can promote transparency about policymakers' financial inclusion plan. If policymakers' financial inclusion communication is done effectively, it increases the credibility and reputation of the policymaker to promote financial inclusion in the eyes of the general public.

More importantly, financial inclusion communication may contain broad statements that reveal less technical details about the plans that are in place to advance financial inclusion. They may also contain hidden sentiments that are not easy to decipher. For the first time, it is now possible to use AI-based large language models to generate

more insight from financial inclusion communications. LLMs are essentially text mining tools that accommodate a large number of parameters (up to billions) and analyse the relationships among words from large volume of texts while taking into account context in summarizing texts (Huang et al, 2022). It is now possible to use large language models (LLMs) (e.g., BERT, ChatGPT, GPT4, XLNet, LLaMA, and T5) to extract summaries, key themes and analyse the sentiments in financial inclusion speeches (Ozili, 2025c). LLMs can be used to filter out the noise and the vagueness in financial inclusion communication.

This study contributes to the literature that use LLMs to analyse policymakers' communications. Presently, policymakers issue statements and speeches on financial inclusion, but the subtle positive or negative sentiments in such statements or speeches remain hidden and are never identified and brought to public knowledge. Also, the literature has not examined the textual analysis of financial inclusion speeches using large language models. Therefore, this study contributes to the literature by identifying ways in which LLMs can be used to enhance the dissemination of financial inclusion communication. It also contributes to the existing literature that examine how LLMs can improve people's lives through insight-gathering from sentiment analysis. It also contribute to the existing literature that examine the role of artificial intelligence in development finance.

The rest of the study is organized as follows. Section 2 presents a conceptual understanding of large language models and the literature review. Section 3 presents some opportunities of LLMs for financial inclusion. Section 4 presents the risks associated with using LLMs in the financial inclusion domain. Section 5 presents the conclusion of the article.

2. Conceptual framework and literature review

2.1. Understanding financial inclusion and its benefits

The literature defined financial inclusion as a process that increase access to basic financial services, increase usage of financial services and increase the quality of financial services delivery (Sarma and Pais, 2011; Ozili, 2025a). The recent literature show that financial inclusion has several benefits. Hassouba (2025) used survey data to examine financial inclusion benefits in Egypt and found that financial inclusion improved the financial lives of poor and low-income groups, and it improved the efficiency of the banking system and contributed to economic growth. However, the challenge to financial inclusion in Egypt is limited outreach to people in underprivileged communities. Ozili (2025b) was interested in financial inclusion dynamics and its effect on economic welfare in the context of the major religions. The author examined the impact of financial inclusion on economic welfare in majority Christian countries, majority Hindu countries and majority Muslim countries. Thirty countries were analysed from 2004 to 2020, and it was found that financial inclusion increased corruption control, political stability, rule of law and regulatory quality in the majority religious countries. A high level of financial inclusion decreased the unemployment rate in majority Muslim countries while a preexisting low unemployment rate increased financial inclusion in majority Christian and Muslim countries.

Wei et al (2025) were concerned about the benefit of digital financial inclusion for e-commerce development and entrepreneurial activity in China. They investigate how digital financial inclusion influences entrepreneurial activity through e-commerce development in China based on data from 275 prefecture-level cities during the 2011 to 2021 period. They found that digital financial inclusion enhances entrepreneurial activity in non-central and non-provincial capital cities. The implication of the result is that policymakers need to leverage digital transformation for within-city entrepreneurial growth and inclusive economic growth in China. Khan et al (2025) explored whether financial inclusion increases remittances and economic growth in developing countries. They analyse 79 developing countries from 2011 to 2021 and found that countries with high levels of financial inclusion witness higher levels of remittances and economic development. Sebai et al (2025) examined the effect of financial

inclusion on financial stability in 26 developing countries from 2004 to 2020 and found that financial inclusion is beneficial for banking stability up to a certain threshold.

Akram et al (2025) were interested in examining whether financial inclusion can prevent women from engaging in financial crimes. They focused on the financial scams and frauds faced by women in the five largest US states by population. They used survey questionnaire to solicit responses from 4,113 women respondents. They found that 94 percent of women believe that financial inclusion can protect them from financial scams and fraud. They also found that financial crimes disproportionately affect women because when women are scammed, they tend to conceal such scam activities from close family members and partners to avoid being shamed. Choudhary et al (2025) investigate the contribution of fintech adoption to financial inclusion and the sustainable development goals. They analyse 86 countries using the quantile regression analysis and found that fintech adoption has a favourable effect on education, gross domestic product and access to the internet at higher quantiles. The implication of the findings is that fintech adoption can accelerate progress towards achieving the SDGs. Rehman and Chen (2025) examined the relationship between financial inclusion and energy intensity in G7 countries from 1993 to 2023. They found that enhanced access to financial services increases access to energy technologies.

Mhlongo (2025) examined the effect of financial inclusion on women entrepreneurship in South Africa. The author noted that lack of access to finance and affordable credit remains a major hindrance to starting and growing a business for women in South Africa with less than 30 percent of women having access to finance to start a business. The author examined whether financial inclusion could increase women's entrepreneurship in South Africa. The author found that financial inclusion improve entrepreneurship by increasing women's participation in business; however, many of the government's financial inclusion programmes do not translate to increased participation of women in business. Fowowe (2025) examined the effect of financial inclusion on agricultural productivity in Mali and found that financial inclusion has a positive effect on agricultural productivity in Mali. The result implies that improving financial inclusion can boost agricultural productivity in Mali. Li et al (2025) investigate the effect of digital financial inclusion on income inequality in the sub-Saharan Africa and found that using the internet and mobile phones to access financial services contribute to a reduction in income inequality in sub-Saharan Africa.

2.2. Understanding large language models

LLMs are a form of generative artificial intelligence. Large language models (LLMs) gained popularity after the emergence of ChatGPT in 2022. They are algorithms that are trained on a large amount of text-based data (such as data from web pages, ebooks, scientific research, media blogs, books or social media posts) which are typically obtained from the open internet (Huang et al, 2022). LLMs always require massive datasets which are sourced from the internet or user interactions, to learn patterns and generate insights or responses (Wu et al, 2024). The algorithms in LLMs analyse the relationship between different large number of texts to produce a probability model (Wu et al, 2024). After producing the probability model, the user can give the algorithm a prompt by asking it a question. The LLM will provide an answer to the question based on the relationship of the texts in the model (Jiang et al, 2020). It is also important to note that the text-based data which are fed into LLMs are static after the model has been trained. However, the LLM can be re-trained or fine-tuned by training it on additional data (Ding et al, 2023). The LLM can also be re-contextualised through a process known as 'prompt augmentation' which is essentially providing context information about the question (Yoo et al, 2021). The greatest advantage of LLMs is their ability to generate convincing content in multiple human and computer languages (Chang et al, 2024). Therefore, users of financial inclusion information, also known as financial inclusion stakeholders, can rely on LLMs to obtain summaries, key themes and sentiments from financial inclusion communication. Examples of existing large language models are ChatGPT, ‘Bard’ owned by Google, ‘LLaMa’ owned by Meta.

2.3. Literature on relationship between artificial intelligence and financial inclusion

Large language model is a type of generative artificial intelligence; therefore, it is important to review the literature on the relationship between artificial intelligence and financial inclusion. Presently, several studies have explored the link between artificial intelligence and financial inclusion. David et al (2025) argued that AI-driven financial technologies can accelerate financial inclusion to increase economic growth and decrease the level of poverty. They argued that AI-assisted fintech apps can offer innovative solutions to accelerate easy access to affordable financial services. The

implication is that AI can assist in delivering a more inclusive financial system. Subramaniam et al (2024) focused on the role of AI adoption for financial inclusion. They investigated the effect of artificial intelligence adoption on financial inclusion. They examined 29 countries from 2017 to 2021. The countries were grouped into low artificial intelligence adopters and high artificial intelligence adopters. The authors used Generalized Method of Moments (GMM) estimations to estimate the effect of artificial intelligence adoption on financial inclusion and found that artificial intelligence adoption is a significant determinant of financial inclusion. They also found that artificial intelligence adoption helped to promote financial inclusion in countries that adopt artificial intelligence. They recommend that artificial intelligence can be deployed to the financial sector to address financial exclusion problems. Fazal et al (2025) also examined the relationship between artificial intelligence and financial inclusion in the context of achieving the United Nations' sustainable development goals by 2030. They argued that financial inclusion is an enabler of 8 of the 17 SDGs. They examined the role of artificial intelligence for achieving financial inclusion and the SDGs. The authors adopted the qualitative research methodology and found that the introduction of artificial intelligence in the financial sector increased people's participation in the formal financial sector and it helped to accelerate economic growth and reduce poverty. Chadha and Gupta (2024) emphasized that there need to be a synergy between artificial intelligence and financial inclusion in order to have an effective financial inclusion model that address financial exclusion problems.

Bhawnra and Singh (2024) focused on India. They acknowledged that, in India, the national financial inclusion scheme, which is the *Pradhan Mantri Jan Dhan Yojana* scheme, was a significant policy intervention by the Indian government to increase financial inclusion. The authors then examined the role of technology, especially artificial intelligence, in the Indian banking sector for the purpose of increasing financial inclusion. They showed that artificial intelligence made significant inroads into specific areas of banking such as risk management and personal financial management, while the most common manifestation of artificial intelligence in banking in India is in developing credit scores for users, developing conversational interfaces such as chatbots, voice recognition, biometric identification, and electronic know-your-customer (KYC) interfaces.

Yang and Lee (2024) also examined the impact of artificial intelligence on financial inclusion. Their study contributed to the literature on artificial intelligence ethics, and it cast some light into how artificial intelligence transparency and accountability affect user outcomes. The authors focused on the ethical aspect of AI, the perceived algorithmic fairness of AI and its effect on financial inclusion. They surveyed 675 users in China and found that perceived algorithmic fairness acts as a significant mediating factor between the ethical attributes of artificial intelligence systems and user responses. They also found that greater artificial intelligence transparency, accountability, and legitimacy enhance users' perceptions of fairness, which, in turn, increases users' satisfaction with AI-assisted financial services and it increases their likelihood of recommending financial services to their friends and family. Jameel and Janjua (2024) also investigated the impact of artificial intelligence (AI)-assisted fintech on digital financial inclusion. They showed that artificial intelligence has a major impact on digital financial inclusion in that it improves risk assessment and mitigation, it assists in generating organised data, it improves cyber security, and it improves fraud detection. The authors recommend that governments, non-governmental organisations, financial institutions and non-financial institutions should embrace artificial intelligence to accelerate financial inclusion. Aishwaryalaxmi and Rathod (2024) were concerned about how artificial intelligence mediates the relationship between digital literacy, digital adoption, and financial inclusion in developing economies. They surveyed 350 participants from developing economies and found that artificial intelligence not only enhances financial decision-making for underserved populations, but it also promotes wider adoption of digital financial services for people who have less financial knowledge. Ozili (2025c) also explored how artificial intelligence can increase digital financial inclusion. The author argued that artificial intelligence can streamline the operations of agents of digital financial inclusion; determine the communal areas in need of digital financial inclusion; automate the digital formal account opening process; offer customized experience for both banked and unbanked adults; ensure security and safety of customers' funds; determine the credit worthiness of unbanked adults who have recently become banked; give banked adults full control of their financial lives; deepen digital financial inclusion; and promote equity and diversity for digital financial inclusion.

2.4. Literature on AI in other financial contexts

Thuraisamy et al (2025) examined the role of generative artificial intelligence in transforming the financial sector and how it can offer innovative solutions and equip the industry with tools to improve operational efficiency in the financial sector. Ally (2025) was concerned about the ability of local legal frameworks to accommodate the complexities brought about by artificial intelligence and smart contracts. Ally (2025) investigated some of the legal challenges affecting the integration of artificial intelligence in the financial sector, focusing on some challenges such as data privacy, cyber security, fraud, consumer protection, algorithmic bias, fairness and transparency. The author also examined the impact of FinTech innovations on Tanzania's legal landscape. The method adopted in the study is the doctrinal legal approach and a comparative analysis of Tanzanian laws, to identify gaps and propose solutions. The study found that existing legal instruments in Tanzania, such as the Cybercrime Act 2015, Electronic Transaction Act 2015 and others, do not adequately address the specific legal challenges posed by artificial intelligence and FinTech. This calls for the development of specialized legal frameworks that accelerate financial inclusion in the digital economy and protect consumers from existing and emerging risks associated with financial technologies.

Saxena and Rishi (2025) were more concerned about how artificial intelligence can transform financial analytics and decision-making processes. They developed the FinSageNet framework which identifies the capabilities of LLM for financial decision making. The FinSageNet framework showed that LLM has the capacity to perform exceptional text summarization, and it outperforms existing LLM models like FLAN and GPT-3.5 in text summarisation. Singh (2025) argued that financial institutions in the United Kingdom can use generative artificial intelligence to address the risk of financial crime and reduce regulatory burden to increase operational efficiency and improve customer experience. Manoharan and Darwish (2025) also examined how artificial intelligence is transforming the financial sector. They showed that AI-based machine learning and deep learning methods are widely used to analyze massive datasets, optimise portfolio, detect fraud, detect patterns, and anticipate risks in the areas of investment banking, asset management, and insurance. They also showed that artificial intelligence has led to the creation of chatbots, robo-advisors, and predictive analytics.

3. Opportunities of LLMs for financial inclusion

LLMs offer several benefits for financial inclusion communications. For instance, LLM can summarise the key themes in financial inclusion communications, it can gain insights from the tone of financial inclusion communications, it can bring discipline to financial inclusion communications, it can improve financial inclusion decision making, and it can enhance the context of financial inclusion text analysis and evaluation.

3.1. Summarizing themes in financial inclusion communications

Many financial inclusion communications are unstructured. LLMs are useful in summarizing the salient themes that are included in unstructured financial inclusion communications. LLMs can summarize lengthy text content, extract key information, and provide concise summaries of financial inclusion communications and speeches (Neekhara et al, 2024). This helps to understand the main points of policy statements, news reports or articles.

3.2. Gain insights from the tone of financial inclusion communications

The policymakers facing significant challenges in achieving their financial inclusion goals will ideally use a less optimistic tone when delivering financial inclusion communications. They may also use a more optimistic tone in financial inclusion communications to mask the challenges they are facing in achieving their financial inclusion goals. As a result, the financial inclusion community may not perceive that there are policy challenges in achieving financial inclusion. Advanced LLMs can analyse the tone used to deliver financial inclusion speeches and generate insights about the challenges, intentionality, genuine enthusiasm and other meanings that are usually hidden in the tone used to deliver financial inclusion communications (Long et al, 2024).

3.3. LLMs can bring discipline to financial inclusion communications

LLMs can analyse the intent behind financial inclusion communication and reveal insight that the authorities do not want the public to know. The frequent use of LLMs to analyse the intent behind financial inclusion communication will be a source of discipline to policymakers that make financial inclusion decisions. LLMs will produce new incentives for policymakers to adopt a more systematic and transparent approach

to financial inclusion communication to preserve their own reputation (Alonso-Robisco and Carbó, 2023).

3.4. Improving financial inclusion decision making

LLMs can assist policymakers to make better informed decisions that improve the financial wellbeing of people. LLMs can quickly process past and present financial inclusion reports and related statistical data to increase policymakers' visibility into overall trends, opinions, common topics discussed, as well as to identify what is working and what is not working, etc. Policymakers can then use these insights to make the most informed financial inclusion decisions based on LLM-assisted data analysis.

3.5. LLMs enhance context-sensitive text analysis and evaluation

LLMs can be used for contextual analysis and evaluation through in-context learning (Hasanbeig et al, 2023). LLMs can be pre-trained on massive amounts of financial inclusion texts and data. The in-context pre-training of LLMs helps to fine-tune the context of text generation and text analysis (Hasanbeig et al, 2023), and it makes LLMs to be context-aware so that it can (i) improve comprehension beyond simple words co-occurrence in financial inclusion speeches, (ii) understand the meanings of words used in financial inclusion contexts, (ii) capture long-range dependencies, (iii) adapt to different financial inclusion problem domains, (iv) and generate texts that make sense in the context of financial inclusion.

4. Risks of LLMs for financial inclusion

A major risk is that LLMs can produce biased interpretations and incorrect meanings after analysing financial inclusion speeches or reports. The biased interpretations and incorrect meanings arise because LLMs are trained on data which tend to favour a specific financial inclusion viewpoint or perspective over other perspectives (Prakash and Roy, 2024; Navigli et al, 2023; Qu and Wang, 2024). Such bias can influence how financial inclusion stakeholders perceive and interpret LLM-based financial inclusion communication. Another concern about LLMs is the privacy risks that arise from the collection of data that are used to train large language models (Pan et al, 2020; Das et al, 2025; Rathod et al, 2025). LLMs can collect and retain large amounts of financial

inclusion data such as speeches, statistics and comments which are sourced from websites, blogs and user social media interactions on the internet, to learn patterns and generate responses. The concern is that the LLM-assisted data collection process may violate the privacy of individuals because the private data of individuals will be collected, incorporated and retained in LLMs without their explicit consent or awareness (Yan et al, 2024). This would constitute unauthorized access to data and the use of unconsented data which is a data privacy risk (Yao et al, 2024). Another concern is that the use of LLMs to analyse financial inclusion communication may spread misinformation and falsehood (Peng et al, 2024; Garry et al, 2024; Sakib et al, 2025). Since LLMs are good at generating the next best syntactically correct word, LLMs can give a false impression that they understand the actual meaning of the words or texts that are commonly used in the financial inclusion domain. Consequently, LLMs can mislead financial inclusion policymakers and stakeholders into believing that the meanings generated from LLMs are the correct meanings. While LLMs generate responses to financial inclusion questions based on accurate syntactic predictions, they do not produce accurate answers based on an actual understanding of what a financial inclusion stakeholder is asking for. Another risk is that LLMs are not a reliable source of information. It is risky to treat LLMs as a knowledge base or to use it to generate information in response to questions. This is because LLMs pose hallucination risks which is the potential for LLM to generate untruthful responses when the trained data, which the LLM uses to answer questions, do not come from a factually correct source. Therefore, LLMs should not be used as a trusted human-like information source.

5. Conclusion

This study identified the benefits and risks of using large language models (LLMs) in the financial inclusion domain. It showed that LLMs can be used to (i) summarize the key themes in financial inclusion communications, (ii) gain insight from the tone of financial inclusion communications, (iii) bring discipline to financial inclusion communications, (iv) improve financial inclusion decision making, and (v) enhance context-sensitive text analysis and evaluation. While large language models have their benefits, they also pose some risks. They can produce biased interpretations and

meanings, and they also pose data privacy risks. They also have the potential to generate untruthful responses when the trained data which the LLM uses to answer questions do not come from a factually correct source. For this reason, there is need for caution and discretion when using LLMs to summarise and understand financial inclusion communications. LLMs should not be used to analyse financial inclusion communications in situations where finding the truth is more important than obtaining syntactic accuracy.

Financial inclusion stakeholders should be careful when using LLMs to analyse financial inclusion policy reports or speeches. They should not view LLMs as a trusted human-like information source. Rather, they should view LLM responses like every other information on the internet which must be vetted and its source authenticated. There is also a need to set clear expectations about the contribution of LLMs to the financial inclusion domain. For example, LLMs are very useful in identifying the major themes in financial inclusion speeches but they are terrible in providing information about the actual number of unbanked adults in a location and no amount of LLM data training, re-training or prompt re-contextualisation will be able to generate the actual number of unbanked adults in a location at any time. This example shows the benefits and risks of LLM in the financial inclusion domain. Therefore, it is not a good idea to use LLMs to generate insights in situations where obtaining the truth is important to inform financial inclusion policy decision. Financial inclusion stakeholders should also consider whether there is any meaningful value in using LLMs to analyse financial inclusion communication.

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