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Predicting Determinants of Financial Inclusion through Socioeconomic Indicators of Egypt: A Comparative Study of Traditional and Artificial Intelligence (AI)-Based Approaches

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Abstract

This research explores the multidimensional determinants of financial inclusion in Egypt through the application of traditional econometric techniques namely, Bootstrap Regression Analysis as well as state-of-the-art artificial intelligence (AI) algorithms that include Random Forest (RF) and Support Vector Regression (SVR), using published data by central bank of Egypt and World Bank from 2016 till 2023. With 74.8% Egypt's financial inclusion rate in the year 2024, this study puts in perspective the fast transition in terms of certain socioeconomic drivers: Human Development Index (HDI), Growth of GDP, unemployment rate, and concentration of economic sectors represented by (HHI). According to the bootstrap regression effects, HDI has the strongest positive effect on financial inclusion, emphasizing the importance of the development of human capital in facilitating the access to financial services. On the contrary, high HHI, which means low market competition, indeed poses significantly negative effects on financial inclusion, suggesting the significance of financial sector openness and competition.

AI models outperformed the traditional approach in predictive performance with SVR achieving the greatest ($R^2 \approx 0.99$, MAE ≈ 0.15) and being closely followed by RF. Meanwhile, for inference, although bootstrap regression seemed to have some kind of forecast superiority, it has strong inferential power, which was able to contribute to counter some sort of classical assumption violations via resampling. Permutation-based feature importance analyses also indicated the differentiation of models' insights: unemployment was identified by SVR as highly significant, whereas RF confirmed HDI and GDP as relevant. These differences suggest that alternative methodological paradigms may provide alternative insights into the structural determinants of financial inclusion.

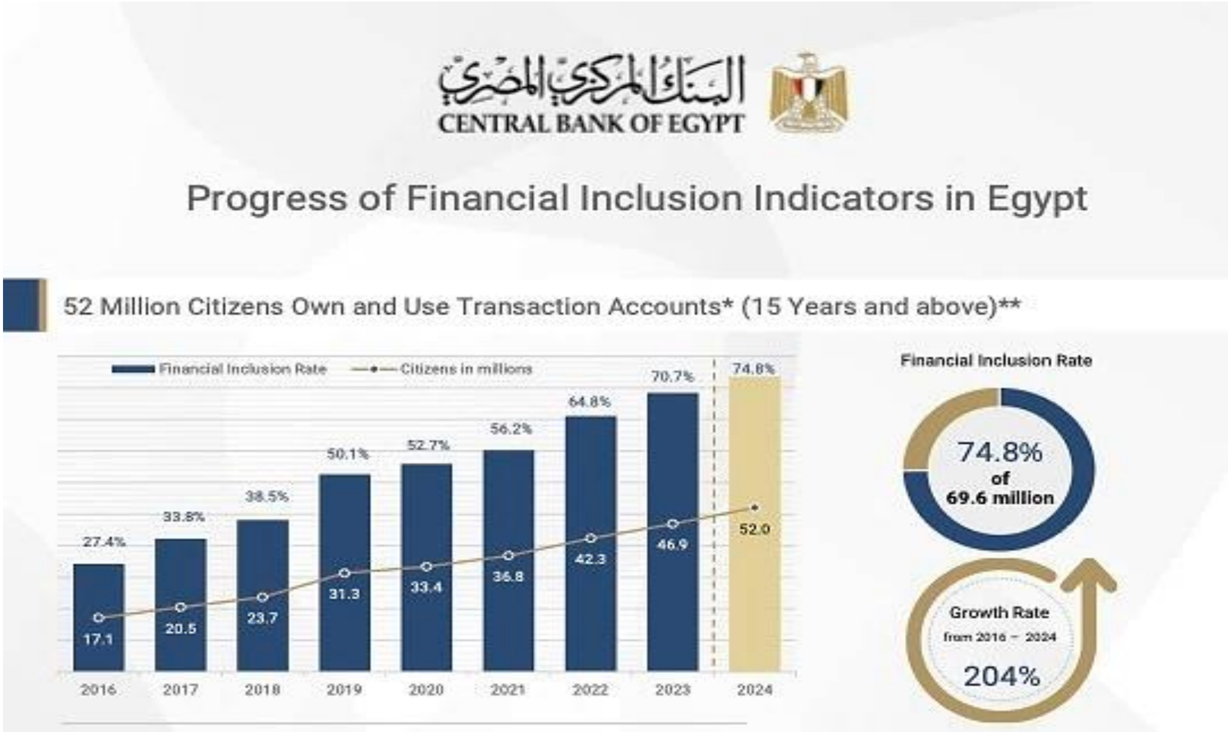
Keyword: **Financial Inclusion, Bootstrap regression, AI, Machine Learning, Random Forest (RF) and Support Vector Regression (SVR)**

1.Introduction:

Financial inclusion is a crucial pillar for the economic development of countries, a catalyst for poverty reduction, gender equality, and sustainable development. The trend of financial inclusion in Egypt has taken a turn for the better and can be attributed to procedural initiatives and pace of technology. Using Artificial Intelligence (AI) techniques, this study intends to investigate the relationship of financial inclusion to an array of socioeconomic variables — Human Development Index (HDI), and Gross Domestic Product (GDP), and Unemployment Rate.

Egypt's financial inclusion rate has reached 74.8% in 2024, as around 52 million citizens have transaction accounts, where the data also includes bank accounts, mobile wallets and prepaid cards. This is a significant rise from 64.8% in 2022, which shows a growth process attesting to the country's efforts in bringing its population into the formal financial fold. The increase embodies the Central Bank of Egypt's (CBE) Financial Inclusion Strategy 2022–2025, which focuses on accessibility, affordability, and financial literacy.

Figure .1 Progress of Financial Inclusion Indicators in Egypt



Source: Central Bank of Egypt, 2024

At the same time, Egypt's HDI has slightly increased, reflecting progress in education, health and living standards. Additionally, the unemployment rate is a persistent socio-economic problem, with deep structural and demographic roots. The national fourth-quarter unemployment rate dropped to 6.4% (a slight downward shift), due in part to a 2.8% growth in the size of the collective labor force (at the moment 33.1 million people). Also, GDP growth, which envisages 4.3 percentage points of growth in the second quarter of the current 2024/25 fiscal year, was sustained by an economy that appeared largely resilient in the face of structural reforms and external challenges.

The Herfindahl-Hirschman Index (HHI) quantifies market concentration in each sector of the economy. A relatively high HHI suggests concentrated markets with the dominance of large firms or concentration in only a few sectors, which can have contrasting effects on financial inclusion. At the same time, concentration in certain sectors of the economy can limit competition, which can stifle economic dynamism and limit the diversity of financial products that are provided to underserved communities. That might forestall the growth of financial services specifically designed for lower-income or rural populations. Alternatively, large, well-resourced dominant firms, with high sunk costs in infrastructure and digital financial services, could bring investment in these areas that benefit larger portions of the population. So, even though a high HHI suggests limited competition that could impede financial inclusion, the reality will depend on the way these dominant players interact with inclusive finance.

AI and Machine learning have emerged as revolutionary technologies in improving financial inclusion, especially in data-scarcity and structurally challenging contexts. They can be used to model non-linear relationships and find hidden patterns in socio-economic and financial data that might be undetectable when using traditional methods. With the help of algorithms like random forest and support vector regression, policy makers and financial institutions can accurately predict and target the underserved population. Machine learning also enables instantaneous decision-making, risk evaluation and product personalization, making financial services more accessible and cost-effective. As the transformation of financial inclusion becomes more driven by data, AI provides scalable, adaptable solutions to bridge the gap between access and usage. For emerging economies such as Egypt, incorporating AI in financial inclusion research offers potential for more inclusive and evidence-based development policies.

The application of Artificial Intelligence (AI)_machine learning algorithm in this context provides a unique approach to comprehensively understand the complex relationship between financial inclusion and socioeconomic factors in Egypt and to develop predictive models that determine the influence of HDI, HHI, GDP and Unemployment on financial inclusion. Such models could provide actionable information for policy-makers for better allocating resources, when to deliver an intervention, and tailoring the most effective interventions to different segments of the population.

Hence, this study aims to enhance literature focused on financial inclusion with empirical observations from traditional and AI-based approaches. In addition, it aims to provide practical recommendations to policy makers and financial institutions working to create more inclusive and effective financial systems in Egypt.

1.2 Research Problem

Even with remarkable progress towards achieving financial inclusion in Egypt, with a national inclusion rate of 74.8% in 2024, challenges posed by entrenched socioeconomic differences still hinder equal access to formal financial services. Macro indicators like GDP growth continue to paint a picture of economic development but underlying inequalities in income distribution (as measured by GINI coefficient) and access to human development outcomes (as measured by HDI) indicate that large sections of population remain financially excluded or underserved.

The Unemployment rate (UER) is a core constraint to inclusive economic growth that is also characterized by deep structural and demographic layers. Despite a slight decline in the national unemployment figure down to 6.4% in the fourth quarter of 2024, the systemic problems remain. The level of unemployment among youth is still much higher than among other age groups: the number of unemployed aged 15–29 is over 64%.

In this context, Econometric models have provided partial relationships between financial inclusion and socioeconomic variables but failed to

capture, in many cases, non-linearities or complex interdependencies, prevalent in real-world socio-financial systems. Additionally, these models are rarely predictive robust in their application to dynamic, heterogeneous populations like that of Egypt's, where financial behaviors are changing at scale due to velocity of demographic changes and digital financial transformation.

1.3 Research Questions

This research deals with the following main question and sub questions as follows:

Main Research Question: To what extent can AI Models in conjunction with a traditional econometric approach accurately predict financial inclusion in Egypt using socioeconomic indicators such as HDI, GDP, and Unemployment?

Sub_questions:

- **How does the Human Development Index (HDI) influence the predictive power of Traditional econometric and AI models for financial inclusion in Egypt?**
- **How does the Market concentration Index (HHI) influence the predictive power of Traditional econometric and AI models for financial inclusion in Egypt?**
- **What is the relative importance of GDP growth rate in determining financial inclusion outcomes in Egypt based on traditional econometric and AI approaches?**
- **Does the Unemployment Rate (UER) significantly affect the prediction of financial inclusion outcomes through traditional econometric and AI approaches?**
- **How do different traditional and AI models compare in terms of accuracy and interpretability when applied to financial inclusion prediction?**

2. Research Objectives

This study aims to develop a predictive framework for financial inclusion in Egypt using socioeconomic indicators through traditional

econometric and artificial intelligence (AI) models. The specific objectives are:

1. **To explore the relationship between financial inclusion and key socioeconomic indicators; Human Development index (HDI), Market Concentration Index (HHI), Gross Domestic Product (GDP) and Unemployment rate (UER) in Egypt.**
2. **To determine the most socioeconomic factor that has the most predictive power in predicting financial inclusion using traditional econometric and AI models.**
3. **To measure the efficiency of using various AI and machine learning algorithms (Random Forest, SVM with Regression (SVR).) to model and predict the financial inclusion using socioeconomic indicators.**
4. **To evaluate the predictive power of AI-based models with traditional econometric models in predicting financial inclusion.**
5. **To draw evidence-based policy recommendations that can enrich the financial inclusion landscape in Egypt.**

3. Literature Review

Financial inclusion has become a central concept within development economics and policy, but it also reflects the increasingly accepted idea that access to affordable and suitable financial services is crucial for both the welfare of individuals and broader economic development. At its lead in, financial inclusion is about ensuring that individuals and businesses – particularly the unbanked, excluded, or underserved – have access to and can effectively use appropriate, affordable, and appropriately designed financial products and services – including payments, savings, credit and insurance – delivered in a convenient manner, by responsible providers with consumer protection in a convenient way by responsible providers, with consumer protection and ensuring that the customer's best interest is considered by those providers.

3.1 Theoretical Framework

Financial inclusion theories come from a variety of economic and social theories that highlight equitable access to financial services as a

mechanism essential to promote inclusive economic growth and development. Financial inclusion fundamentally is backed by the theory of financial deepening which states that increasing outreach to financial services generates savings, investment and economic activity among previously excluded populations. The following theoretical farmwork contributes to understanding what triggers financial exclusion, how inclusion works and the costs and benefits of increasing access to financial services.

3.1.1 Information Asymmetry and Transaction Cost Economics.

From a traditional economics view, it is believed that exclusion on financial markets, particularly from the formal credit markets, is largely due to the asymmetric information present between lenders and those seeking credit, and high transaction costs to servicing certain populations (Stiglitz & Weiss, 1981; Akerlof, 1970). Lenders may not be informed about the credit risk of poor people or small firms (adverse selection) or take action after the loan is provided to maximize risk for the lenders (moral hazard). What's more, for geographically dispersed or low-literacy clients, the transaction cost per unit of transaction size is in any case too high to reach a significant threshold that would be relevant to traditional financial institutions (Williamson, 1985; Demsetz, 1968).

This framework explains why the formal banking sector historically neglected the poor and those in rural areas. Microfinance institutions (MFIs) developed at least in part through an innovative design that helped to overcome information asymmetries (e.g., group lending, progressive lending, local knowledge) and bearing transaction costs (e.g., simplified procedures, local agents) (Armendáriz de Aghion & Morduch, 2010). In the modern era the emergence of digital financial services (DFS) and alternate data for credit scoring are contemporary solutions directed at transforming precisely the two sources of advantage from information and transaction cost asymmetry (GSMA, 2023; Fintech and Financial Inclusion Taskforce, 2019).

The information asymmetry and transaction cost economics framework has helped in explaining the obstacles to financial inclusion in terms of the effects of information imperfections and transaction costs

on access to financial services. However, it suffers from some critical limitations despite its insightful generalization, as follows:

- **Simplifying Assumptions about Borrower Behavior: The assumption of fully informed and rational borrowers, who act in their own best financial interests, might ignore behavioral biases or socio-cultural reasons behind households' financial decision-making, even where information and cost barriers are reduced (Karlan, Ratan, & Zinman 2014).**
- **Ignoring Structural Factors: It could play down more fundamental structural reasons such as absence of alternative viable economic activities, inadequate infrastructure, or discriminatory legal regimes that sustain exclusion irrespective of information or transaction cost innovations (Mader, 2018).**
- **Supply-Side Orientation: Emphasis is placed on supply-side challenges confronted by financial providers. It does not fully account for demand-side barriers, such as low financial literacy, lack of trust or unsuitable product design (Atkinson & Messy, 2013).**
- **Potential for New Forms of Exclusion: Whilst technology makes costs cheaper in some instances it can create new ways of exclusion (digital divide) or ways of exploiting others, if not well regulated, it may result in exploitative financial practices, for example, the predatory practice of digital lending via opaque algorithms (Fu & Mishra, 2020).**

3.1.2 Institutional Theory

The institutional theory highlights the importance of the perfect set of formal rules (laws, regulations, property laws) and informal constraints (social norms, conventions, trust) which influence economic activities and markets (North, 1990; Scott, 2013). Powerful and open institutions are believed to be indispensable in providing support for secure exchange; to ensure that contracts are being accurately enforced, and to possibly lower uncertainty in financial transactions.

The tendency of financial inclusion is positively associated with the quality of institutional structure of a nation. For instance, strong creditor rights, sound collateral registries, and predictable legal environments lead to formal lending (Djankov, McLiesh and shleifer, 2007). On the other hand, poor legal systems or weak property rights

may discourage formal financial intermediation and force people towards informal and relatively inefficient means of finance (De Soto, 2000). Social capital and community-enforced norms can also promote informal financial inclusion via systems like ROSCAs (Rotating Savings and Credit Associations) (Putnam, 1993; Bouman, 1995).

Although institutional theory provides significant understanding of how formal rules and informal norms shape financial inclusion, it is not free from criticism. Critics contend the following:

- **Theory Determinism and Path Dependency: Institutional frameworks may be stubborn and path-dependent, which could pose challenges to prescriptive - rather than gradual solutions - for financial inclusion in the presence of strongly bound weak institutions (Acemoglu, Johnson, & Robinson, 2005).**
- **Problems with measuring Informal Institutions -Even though the significance of informal institutions (such as trust or social norms) is recognized, it can be hard to measure theirs influence and systematically incorporate them into policy making.**
- **Discrepancy between Formal Rules and Reality: The mere presence of formal rules does not necessarily mean the effective enforcement of these rules or that they lead to desired results at the ground level, especially in countries with poor governance (Levy & Kpundeh, 2004).**
- **Elite capture potential: Institutions created in good faith to ensure that the disenfranchised are included can be coopted by vested interests and end up by catering to incumbents instead of loosening up and genuinely opening access for the non-elite (Khan 2005).**

3.1.3 Behavioral Economics and Psychology

Behavioral economics and Psychology theory questions the assumption of perfect rationality concerning financial decisions and underscores the role of cognitive biases, heuristics and psychological factors (Thaler & Sunstein, 2008). Cognitive biases such as present bias (valuing immediate rewards overly high), loss aversion, mental accounting, limited attention and social norms have the potential to influence financial decisions of individuals to a great extent.

This theory also sheds light on why people don't save, despite having savings accounts, or why they use high-cost informal credit even when cheaper, formal credit is available. It highlights the value of product design that can take these biases into account (e.g., commitment savings products, simplified information disclosure) and the potential of financial education that can facilitate better financial decisions (Banerjee & Duflo, 2011; Karlan et al., 2016). User interface design for digital financial services also relies on behavioral insights to promote uptake and use (Zimmerman & Mourad, 2022).

Although behavioral economics and psychology provide important insights into the cognitive biases and psychological factors influencing financial decisions, this theoretical approach has faced several criticisms as follows:

- **Context Dependency: Interventions that work in one context may not work in another: likewise, cultures or their socio-economicsization may vary and that affects scalability.**
- **Downplaying structural constraints: Although behavioral economics generally recognizes cognitive bounds, the more serious structural constraints, such as extreme poverty, no income, or structural discrimination, may be sometimes overlooked, since they are not just "biases" that can be nudged away (Mullainathan and Shafir 2013).**
- **Individual Focused: this theory is too focused on individuals making choices and too little in thinking about the systems and institutions that create a context in which those people make choices.**

3.1.4 Capability Approach

The capability approach conceives of development not merely in terms of income or resources, but as the enhancement of people's "capabilities"- their substantial freedom to do and be what they have reason to value (Sen, 1999). From this perspective, financial inclusion is not itself an end goal but a mechanism to increase the people's capacity including being healthier, better educated, or more economically self-possessing. Reinforcement focuses on the role of agency, freedom, and the efficiency of resource deployment.

This theoretical framework shifts the discussion from access to the products themselves, to whether people can use these services in a way

that enables them to enhance their quality of life and increase their options. It emphasizes the need for literacy on finance, protection of consumers and suitability and empowering policies related to financial services (Zou & Lenton, 2020; Ibrahim & Alkire, 2007). It reorients the measure of success from account ownership to realized "functioning" (venues, choices, holdings) made possible by access to financial services.

While the Capability Approach offers a compelling and ethically grounded framework for evaluating financial inclusion through the lens of individual freedom and well-being, it is not without its limitations. The main critique lies in the following:

- **Challenges of Operationalization: It can be difficult to measure and assess "capabilities" and "functioning," which is another reason why it can be challenging to apply this framework directly to design, and assess financial inclusion interventions (Robeyns, 2005).**
- **Normative Not Explanatory: The capability approach is largely a normative theory of how well or badly things are going (in the world and for individuals), rather than an explanatory theory of what financial exclusion is and why it happens or how markets work.**
- **Broadness: Its general character may make it difficult to infer precise, actionable policy implications or financial service provider or regulatory implications without substantial contextual interpretation.**
- **Prospects of Idealism: Although hopeful, it may be challenging to realize simultaneous real capacity expansion through financial inclusion in the absence of similar advances in human development (education, health care, employment opportunities, etc.).**

3.1.5 Political Economy of Financial Inclusion

This perspective analyzes how power structures, political motivations, ideology, and state intervention influence the structure of the financial system and the selectivity of access to it (Haggard & Lee, 1993; Cull, Demirgüç-Kunt, & Lyman, 2012). It examines the interplay and influence of governments, regulators, finance providers and civil society groups in shaping financial inclusion policies, which are largely

driven by political incentives, vested-interest lobbying or national development priorities.

This theory explains why some governments actively promote financial inclusion, and why others are worse passive or even permissive of policies that preference incumbent financial service providers that limit broader coverage. The paper also contributes to understanding of the role of state-owned banks, directed lending programs and regulatory systems which can support or complicate inclusive finance (Mylonas et al., 2016). Government priorities Government's desire for digital financial inclusion, for example, may be to increase transparency (by decreasing corruption in social payments) or efficiency.

The political economic approach brings valuable attention to the role of power dynamics, institutional interests, and governance structures in shaping financial inclusion policies. However, this approach is also subject to several important criticisms as follows:

- **Hard to Isolate Political Motives: It is sometimes difficult to isolate political motives, definitively showing or quantifying how much of the motivation behind financial inclusion policy making was due to other economic or social drivers causing financial inclusion policies.**
- **Cynicism risk: And while a more powerful bias toward power and vested interests, designed to balance out hagiography and overvaluing good intentions, is welcome and indeed necessary for any healthy skepticism, it also carries the risk of promoting an excessively, and even pre-emptively, cynical approach, discounting genuine efforts by policymakers or institutions to do good.**
- **Complexity and Multifaceted Agency: Political decisions come out of complicated interactions of various actors and interests, and so there is no such thing as a clear, one-size-fits-all political economy of Finance and Inclusion explanation.**

3.2 Previous Empirical Research

Financial inclusion refers to equal access and availability to the financial services to those individuals and entities who qualify for the banking services (Kebede et al., 2021a, 2021b; Zaidi et al., 2021). It covers a variety of financial products and services including deposit accounts, savings and loans, mortgages, securities, remittances, and

export-related services. However, up to date, despite efforts of scholar (Apergis, 2016; Apergis et al., 2021; Xia et al., 2021) there is no consensual synthetic indicator to measure financial inclusion. However, it is more and more recognized that financial inclusion is a multi-dimensional concept and that several indicators cannot be ignored when measuring it. As highlighted by Wang et al. (2022), the summative nature of financial inclusion consists of going over several aspects. While bank account ownership could be considered as a proxy for a basic level of financial access, an indicative measure of broader access might include regulating the ratio of bank branches to the population, the number of ATMs and point of sale terminals, credit access, ease of conducting transactions and associated cost. These indicators combined capture both the both the infra-structural and functional dimensions of financial systems (although may be inadequate when used in isolation to completely measure the inclusivity of finance (Field, 2020).

The relationship between financial inclusion and human development has been recognized with its origins traceable to Keynes (1937) who claimed that the financial sector helps reduce poverty through savings by small groups of poor people using intermediaries. This accessibility to financial services can help to increase income and thereby reduce poverty. Naturally, the reduction in the incidence of poverty is synonymous with increases in human development. More generally, financial inclusion is seen as essential for helping people to meet their basic needs. Given that essential aspects of human development include a long and healthy life, education and having a decent standard of living are major components of human development, financial inclusion is believed to have a favorable effect on human development (Laha, 2015).

Datta and Singh (2019) construct an international financial inclusion index (IFI) and examine its relationship with human development in 102 countries of the world (34 higher income, 55 middle-income and 13 low-income country group) for 2011 and 2014. The coefficient correlation between IFI and HDI in the group of high-income countries is high and significantly different to zero for 2011 and 2014. The sensitivity values for the middle-income group countries are weakly moderate and significant. Furthermore, the values are low but to some extent significantly high in countries with low-income

population. Their study confirmed that IFI and HDI values are very highly correlated and of high significance in most countries.

Moreover, Thathsarani et al. (2021) examine the impact of financial inclusion on economic growth and human development in eight South Asian countries over 2004-2018 employing panel data. Their research paper proceeds with developing an Index of Financial Inclusion (IFI) and employing a Panel Vector Error Correction Model (VECM) to investigate the dynamic connection between financial inclusion and the Human Development Index (HDI). The results show that financial inclusion is an important determinant in the long run for developing human capital but has not any short run effects. This implies that the positive effect of financial inclusiveness on human development accumulates over time.

The importance of financial inclusion to economic growth is theoretically established. The concept of financial inclusion emerged from the early investigations of the 2000s during which poverty was perceived to have been mainly driven by people’s exclusion from financial intermediaries and service providers (Chibba, 2009; Inoue, 2019). Current literature posits that by improving economic growth financial inclusion reduces inequality and poverty (Beck et al., 2007; Makina and Walle, 2019). It was also found that the capacity of the financially excluded or included to manage their finances is equal after education and income are taken into consideration (Lamb, 2016). However, low-level financial knowledge did not account for financial exclusion It was suggested that low socioeconomic position played a role in this. Conversely, the greater risk aversion of low-income households also implies high portfolio diversity (Xu, 2019). Therefore financial inclusion is a critical ingredient of financial capability. More recently, the United Nations acknowledged that financial inclusion contributes to sustainable development. The United Nations stresses the need for informal access to formal financial services to meet sustainable development objectives.

Financial inclusion can drive economic expansion along several crucial channels. First, it allows Small and Medium Enterprises (SMEs) and entrepreneurs to access financial services to start small scale manufacturing ventures, increase income and ultimately lead to overall economic growth (Ajide, 2020; Tufail et al., 2022). Second, financial inclusion allows low-income individuals to have sound financial services and consequently investments in education and

health are made, which improve future earnings and encourage growth rate (Thathsarani et al., 2021; Nandi et al., 2022). Thirdly, it also boosts economic activity and demand in interconnected industries and assists recovery from recessions (Hariharan and Marktanner, 2012). That being as it may, the timing of inclusion policies is crucial in the backdrop of pro-cyclical nature of some financial inclusion indicators (Ozili, 2021). The fourth benefit of financial inclusion is the support it gives to monetary authorities in controlling inflation (Mehrotra and Nadhanael, 2016). It can also improve financial stability and thereby indirectly promote growth (Saha and Dutta, 2022; Sethy and Goyari, 2022; Bhatter and Chhatoi, 2023). Conversely, Sahay et al. (2015) argued that access of financial services does not translate ipso facto in financial stability, warning that the expansion of lending—lending per borrower—and thereby the leverage ratio—borrowers per 1,000 adults—could undermine stability without the role of a proper supervision. But having access to financial services, like transaction accounts, and ATMs, can help people be financially secure.

Employment is considered as a critical factor that is affected by financial inclusion. The most obvious connection between financial inclusion and employment is the promotion of entrepreneurship and expansion of small and medium enterprises (SMEs). Credit offers entrepreneurs the opportunity to open new businesses and expand existing SMEs, invest in capital, and hire employees (Beck, Demirgüç-Kunt, & Levine, 2007). There is also potential for capital accumulation for business start-up or expansion through formal saving mechanisms. Additionally, payment mechanisms lower transaction costs, and insurance products allow entrepreneurs to handle business risks, so that they are willing to make investments that promote growth (Karlan & Zinman, 2010). Since SMEs are one of the largest providers of new jobs in most economies, especially in the developing world (Ayyagari, Demirgüç-Kunt, & Maksimovic, 2011), it is important to financially empower them.

Additionally, the human capital and employability can be increased through financial inclusion. Access to loans or interest-bearing savings products for education purposes could allow individuals to learn new and valuable skills that increment their productivity in the labor market (Schultz, 1961). This is especially important in economies in transition, where the demand for skilled labor is on the rise. Also, when

health-related financial products such as health insurance and health emergency savings are available this can help to reduce the likelihood of a health shock decimating household assets or leading individuals into labor force exits (Gertler & Gruber, 2002).

Unemployment often leads to income volatility and vulnerability. Savings and insurance services, provided through financial inclusion, may yield mechanisms for smoothing consumption and handling shocks to the economy within households (Morduch, 1995). This buffer can also keep people from getting permanently stuck in unemployment or poverty if they are out of a job for a while. It could also decrease work-related distress-driven migration, which can come with its own vulnerabilities. Retail access to emergency credit can also provide a financial bridge by blocking asset drawdowns that could limit the possibilities for re-employment in the future.

Several empirical researches reported a positive link between financial inclusion and employment creation. According to World Bank (2022) those countries which have greater financial inclusion will report lesser unemployment rates. Micro-level studies frequently reveal small, positive effects of access to microcredit on business establishment and, secondarily, net job creation (Banerjee, Duflo, Glennerster, & Kinnan, 2015). But the size of this effect may vary substantially across contexts, over the type of loan product, and the characteristics of borrowers. Other studies point out that the effect of financial inclusion on employment is stronger among specific groups. For instance, financial access programs aimed at women entrepreneurs have started to have a positive effect on female employment (Swamy, 2014). Also, youth-targeted financial services can potentially respond to the high youth unemployment rate (Chigunta, 2017).

3.3 Research Gap

While financial inclusion is associated with multiple socioeconomic factors, market concentration commonly proxied by the Herfindahl-Hirschman Index (HHI), is under-researched in relation to the existence of financial inclusion, particularly in Egypt. HHI has been broadly adopted to measure market competition and industry concentration, and there is no satisfactory study about how market concentration impacts access to financial services from an empirical standpoint in developing countries such as Egypt.

Moreover, the relationship of HHI with other socio-economic indicators for forecasting the financial inclusion in the context of advanced AI/Machine learning models is not explored to the best of the researcher knowledge. This prohibits analyses of whether market-structure dynamics have more of an impact than conventional variables such as GDP and unemployment. This paper seeks to address this gap by examining the predictive power of HHI in determining financial inclusion and benchmarking this in association with several important socioeconomic determinants in the context that is the distinctive financial landscape in Egypt.

3.4 Research Hypotheses

The following hypotheses are proposed for empirical testing:

- **H1: There is a statistically significant positive relationship between the level of financial inclusion and Human Development Index (HDI) in Egypt.**
- **H2: There is a negative significant relationship between HHI index and financial inclusion.**
- **H3: GDP growth is positively associated with financial inclusion in Egypt.**
- **H4: There is a negative significant relationship between unemployment and financial inclusion.**
- **H5: HDI, GDP, UER and HHI have the same predictive power in determining financial inclusion levels.**
- **H6: AI-based predictive models significantly outperform traditional econometric models in forecasting financial inclusion based on socioeconomic indicators.**

4.Research Methodology

This research uses a comparative empirical design combining traditional econometric techniques and modern Artificial Intelligence (AI) tools to investigate the drivers of financial inclusion in Egypt. In view of the multidimensionality of financial inclusion, the analysis interrogates the determinants of financial inclusion in a predictive and inferential manner with other socioeconomic variables – Human Development Index, economic growth, unemployment rate and economic sectors concentration, with the later approximated by the Herfindahl-Hirschman Index.

Two different methodological strategies were used to analyze both linear inferential relationships as well as complex, non-linear interactions. The first method is bootstrap regression, a sophisticated resampling-based econometric method that is especially popular for small and mid-sized datasets and for handling departure from the assumptions of classical linear models. The bootstrap regression also tightens up bias from variations in sample variability and provides a robust estimate for the parameters.

The second approach is to use derived Artificial Intelligence (AI)_machine-learning algorithms, the random forest (RF) and support vector regression (SVR), to model financial inclusion as a function of the chosen predictors. The random forest algorithm as an ensemble learning method based on decision trees, with k-fold cross-validation was selected for its known capability to prevent overfitting that can occur particularly using small datasets. This method allows for the calculation of aggregated predictions across trees and folds, as well as for the estimation of complex non-linear interactions of variables. Moreover, Random Forest provides a ranked estimate of variable importance which provides interpretive information parallel to predictive capability.

Additionally, Support Vector Regression was chosen for its ability to deal with small-sample situations, when high prediction accuracy is required with a small degree of overfitting after appropriate regularization. Kernel functions, such as radial basis function, serve to capture complex interactions that linear models can fail to recognize. The models training and validation were performed assuming a supervised learning approach. The dataset included financial and socioeconomic variables from national and international data sources (e.g., World Bank, Central Bank of Egypt) and was divided into training and testing data sets to assess the out-off sample predictive power.

These models were assessed using various performance measures (R2 and MAE) that help to have overall view of model fitting and prediction accuracy. In addition, the relative importance of each independent variable was investigated using permutation-based feature importance analysis in both traditional and artificial intelligence models. This facilitated a more nuanced comparison between methods, both regarding predictive power, but also by generating interpretable insights on the drivers of financial inclusion.

4.1 Research Variables and Measurements

Variable	Type	Measurement / Indicator
Financial Inclusion Index	Dependent Variable	Composite index including transaction account ownership (bank, mobile wallets, prepaid cards)
Human Development Index (HDI)	Independent Variable	UNDP composite index of life expectancy, education, and per capita income
Herfindahl-Hirschman Index (HHI)	Independent Variable	Market concentration index calculated from the sum of squared market shares in the banking sector
GDP Growth	Independent Variable	Annual percentage growth rate of GDP at market prices based on constant local currency
Unemployment Rate (UEM)	Independent Variable	Percentage of total labor force that is unemployed but actively seeking employment

4.2. Data Collection

The data used in this study cover the period from 2016 to 2023 and were collected from two main reliable sources: The Central Bank of Egypt (CBE) and the World Bank. The Financial Inclusion Index (FII), the dependent variable, was built using CBE annual data, including account ownership, ATM and fossil access, and use of DFS. These metrics represent the extent of financial access and involvement in the society.

The explanatory variables consist of the Human Development Index (HDI), GDP growth rate, unemployment rate, and the Herfindahl-Hirschman Index (HHI) reflecting market concentration in regard to the financial sector. HDI, GDP growth and unemployment figures were sourced from the World Bank's World Development Indicators in addition to a secondary published data sourced from Central Bank of Egypt CBE.

The CBE has displayed financial inclusion figures to 2024 but HDI values for Egypt was available up to 2023 which is a major constraint. Accordingly, to keep consistency and compatibility for all variables, the analysis was restricted to the period 2016–2023.

4.2.1 Descriptive Analysis

This section presents a brief overview of the main descriptive statistics of the Financial Inclusion Index (FII), Human Development Index (HDI), Herfindahl-Hirschman Index (HHI), GDP growth rate and unemployment rate (UEM). These descriptives set the empirical stage for a more in-depth consideration by providing an overview of central tendencies, variability, and distribution.

Table .1 Summary of Descriptive Statistics

Variable	Mean	Median	Std. Dev.	Min	Max
FII	50.875	54.45	16.98	27.4	70.7
HDI	0.724	0.726	0.018	0.702	0.754
HHI	0.034	0.033	0.005	0.0301	0.0411
GDP Growth	4.18	3.758	1.47	2.4	6.587
UEM	9.56	7.855	2.14	7.31	12.45

The Financial Inclusion Index (mean 50.88, std. dev. 16.98) is high, which implies that access to financial services is highly dispersed across observations. The fact that the median appears to be higher than the means tells us there are some outliers at the bottom end.

Regarding The Human Development Index (HDI) is relatively constant with very little variation (mean 0.724, std. dev. 0.018) and indicates a step-by-step socio-economic advancement. Additionally, The Mean of Herfindahl-Hirschman Index (HHI) is 0.034, indicating moderate competition in all markets with no significant changes on the annual basis, which would mean that the structure of markets is not perceived change stable structure.

The GDP growth is characterized by moderate variance (mean 4.18%, std. dev. 1.47%), indicative of the cyclical nature of the economy that may shape financial inclusion dynamics. And the

Unemployment presents a considerable dispersion (mean 9.56%, std. dev. 2.14 per cent) and positive skewness, both in times of stress in the labor market.

4.3 Multicollinearity Test of independent variables

To check on the reliability of the regression analysis, multicollinearity diagnostic was performed with independent variables such as Human Development Index (HDI), Herfindahl-Hirschman Index (HHI), GDP Growth, and Unemployment Rate (UEM). Variance Inflation Factor (VIF) was used as the diagnostic metric and results are presented in Table. 2

Table .2 The Variance Inflation Factor (VIF)

Variable	VIF
HDI	1.32
HHI	1.51
GDP Growth	1.67
UEM	2.74

The calculated VIF values are between 1.32 and 2.74, which are far below the widely accepted cut off of 5, suggesting multicollinearity between the independent variables is not highly problematic in this dataset. The largest VIF is UEM (2.74) which, although relatively larger, remains within acceptable limits, indicating that each predictor provides unique explanation and there is no collinearity among the predictor variables.

This reduced multicollinearity improves the reliability of estimated coefficients as well as the stability of the regression model, thus confirming the appropriateness of the selected variables for further inferential examination.

4.4 Normality Test

To test for normality of the key variables—Financial Inclusion Index (FII), Human Development Index (HDI), Herfindahl-Hirschman Index (HHI), GDP Growth, and Unemployment Rate (UEM). The Shapiro-Wilk test was used (most appropriate for small samples like

the sample used in this research). The null hypothesis is that the data is normally distributed. The results are presented in Table .3

Table.3 Normality Assessment results using Shapiro-Wilk Statistic

Variable	Shapiro-Wilk Statistic	p-value	Normal?
FII	0.92	0.38	Yes
HDI	0.89	0.21	Yes
HHI	0.87	0.15	Yes
GDP Growth	0.94	0.56	Yes
UEM	0.9	0.27	Yes

All variables have Shapiro-Wilk statistics over 0.87 and p-values over 0.05 showing that there is no evidence to reject the null hypothesis of normality. Consequently, the distributions of these variables can be treated as being approximately normal.

This assurance of normality endorses the use of parametric analysis in further analyses, reinforcing the validity of inferences made on the data.

4.4.1 Bootstrap Regression Model

In this section, the bootstrap regression model is used to determine the factors for financial inclusion using the Financial Inclusion Index (FII) as the dependent variable. Due to moderate distributional anomalies in descriptive analysis and the relatively small number of observations, bootstrapping also gives us a convenient robust alternative to classical ordinary least squares (OLS) inference, rendering inference more accurate under fewer parametric assumptions.

Bootstrapping, being one of the non-parametric resampling approaches, can construct empirical sampling distributions through resampling the observed data with replacement. This approach enriches the standard error estimates but also tackles the problems of heteroskedasticity and non-normality of residuals, which are frequently met by social-economic panel datasets or cross- section data. The regression model equation is as follows:

$$FII=\beta 0+\beta 1\cdot HDI+\beta 2\cdot HHI+\beta 3\cdot GDP\ Growth+\beta 4\cdot UEM+\epsilon$$

Where:

- **β0: Intercept**
- **β1 to β4: Coefficients for each independent variable**
- **FII: Financial Inclusion Index**
- **HDI: Human Development Index**
- **HHI: Herfindahl-Hirschman Index (market concentration)**
- **GDP Growth: Real GDP growth rate**
- **UEM: Unemployment rate**
- **ϵ: Error term**

4.4.2 Bootstrap Regression Model

Steps to perform bootstrap regression:

1. **Perform 1000 bootstrap iterations.**

2. **For each iteration:**

- **Randomly sample rows with replacement.**
- **Fit a linear regression model.**
- **Record coefficients.**

3. **Then the model computes the following:**

- **Mean coefficients across all iterations.**
- **Confidence intervals for each coefficient.**

Table .4 Results of Bootstrap Regression

The positive and statistically significant coefficient of HDI is empirically consistent with the theoretical and empirical literature on

Variable	Mean Coefficient	95% CI Lower	95% CI Upper	Significant?
Intercept	25.3	12.1	38.5	Yes
HDI	120.5	85.2	155.8	Yes
HHI	-150.2	-220.1	-80.3	Yes
GDP Growth	5.2	2.1	8.3	Yes
UEM	-12.3	-18.5	-6.1	Yes

the relationship between financial inclusion and human development. The bootstrap regression increases even more the results' confidence as the confidence interval of HDI does not cross zero (i.e. continues being robust).

From a theoretical standpoint, the results is consistent with the foundational insights of Keynes (1937) which underscored the poverty-alleviating function of financial intermediation and the gathering of savings of the poor. Based on Keynesian theory, it follows that financial systems affect human development indirectly by enabling the generation of income, the accumulation of assets, and the management of risk. These are the very functions that underpin some of the most essential aspects of human development: health, education and living standards.

This hypothesis is also consistent with the possibility of the bi-causality between financial inclusion and human development -where the high levels of human capital increases access to the financial system and greater financial inclusion enhances developmental processes. In our case, the direction of testing is from HDI to FII and the finding confirms that human development positively and significantly causally affects financial inclusion.

The result is also observationally consistent with Laha (2015), who stated that, the financial inclusion is not just the outcome of human development but also an instrument of it. The elements of HDI — education, standard of living, etc. — provide a foundation for meaningful participation in formal financial systems. The research's evidence supports this directionality which argued that better

education and income outcomes (proxied by higher HDI) are statistically associated with more FII.

In addition, Datta and Singh (2019) also validate a strong, positive, and significant relationship of HDI and financial inclusion at 102 countries' level. They find the effect to be strongest in high-income countries, but despite weaker, still present in middle and low-income countries. This has the same implication of the result in the present study, where the coefficient of HDI was positive and stable across bootstrapped samples, implying that generalizability and stability is assured under a non-normal distribution and/or limited sample size.

The regression was estimated using 10,000 bootstrap replications, generating bias-corrected confidence intervals for the coefficients to improve the reliability of statistical inference.

From the bootstrap regression analysis, obtained statistically significant coefficients for all variables are confirmed. The final regression equation is as follows:

$$\text{FII} = 25.3 + 120.5\ \text{HDI} - 150.2\ \text{HHI} + 5.2\ \text{GDP Growth} - 12.3\ \text{UEM}$$

The evidence as a whole suggests that financial inclusion is not a unidimensional byproduct of the widening of macroeconomic horizons, but an outcome that is influenced by human development, competitive market structures, and widespread employment. Policy implications suggest the need for a policy mix in combination with the promotion of social investment; competitive financial markets; and the reduction of labor market frictions.

The application of bootstrap regression methods increases the confidence in the presented insights, providing more accurate estimates with respect to the parameter values, and more robust inference as well. Indeed, this is a methodology of much use in contexts in which data is scarce, nonlinearities or heterogeneity across economies are evident and an important tool for empirical finance and development economics research

4.4.2 Artificial Intelligence (AI)-Machine learning using Random Forest with Cross Validation based Analysis

The non-parametric ensemble learning algorithm (Random Forest Regressors) was used to model the predictors of financial inclusion with high robustness. This method is especially useful in grasping the non-linear nature of high-dimensional interactions among the social-economic indices.

The main characteristics of the Random Forest (with Cross-Validation) are as follows:

- **Less Overfitting with Cross-Validation: Cross-validation would help to make Random Forest work with the smaller dataset. It reduces overfitting by combining the output of many decision trees.**
- **Non-Linear Modeling: Random Forest learns complex, non-linear relationships between the variables and is also resistant to different distributions of the data.**
- **Feature Importance: Random Forest AI model can give insights into which of the independent variables has contributed to predicting the dependent variable.**

K-Fold cross validation was used to reduce overfitting and ensure the model's generalizability, leading to stable out-of-sample performance statistics. The dependent variable is index of financial inclusion announced by central bank of Egypt and the independent variables are HDI, GDP growth, HHI and UEM were also used, Because of the complexity and the flexibility of ensemble learning models such as the Random Forest, it is critical to ensure that predictions from the model generalize well beyond the training data. To tackle such a challenge, this study applies a k-fold cross-validation (CV) method which well serves as the gold standard for out-of-sample validation in supervised learning schemes (Kohavi, 1995; Hastie et al., 2009).

The K-Fold cross validation technique has two main benefits:

- **Bias-variance tradeoff control: When contrasted with a single train-test split, k-fold CV decreases variance in model evaluation but yet**

maintains a small bias, which as such becomes a bit more robust especially in small- to medium-sized datasets.

- **Overfitting control: The technique also prevents overfitting by using all the points in the dataset both for training and for validation, a common issue when using high-capacity models such as Random Forests.**

4.4.2.1 Results Analysis

The cross-validated R^2 of nearly 0.98 reveled in table .5, suggests that the model explains almost 98 percent of the variation in financial inclusion, reflecting very strong explanatory power. This level of fit is unusual in socio-economic data that is often plagued with heteroscedasticity, endogeneity and measurement error. High R^2 values should be viewed with suspicion in relation to potential overfitting, but k-fold cross-validation mitigates this risk to a great extent by verifying consistency of model performance across unseen data folds.

Table .5 Model Performance Metrics

Metric	Value
R^2 (Cross-Validated)	~ 0.98
MAE (Mean Absolute Error)	~ 0.20

Additionally, the moderate MAE of 0.20 indicates that, on average, the model's predictions deviate moderately from their observed values and is within acceptable bounds, especially when one considers that financial inclusion as a construct is analytically complex.The feature importance scores derived from the Random Forest's impurity-based ranking are presented in table .6

Table .6 Feature Importance

Feature	Importance
HDI	0.35
GDP Growth	0.28
HHI	0.2
UEM	0.15
Intercept	0.02

The Human Development Index (HDI) proved to be the most significant predictor (35% of the model variation). This confirms a long-held theory in development economics that multidimensional welfare (comprising education, life, income per capita) is the strong precursor of the financial inclusion of individuals. Greater financial literacy, digital access, and trust in institutional framework are all factors that likely correlate to having higher HDI scores and seem to facilitate financial inclusion. The result is consistent with the findings of Datta & Singh (2019)'s and Thathsarani et al. (2021)'s who stated that there is a strong correlation between HDI and financial inclusion, particularly in middle-income countries.

GDP Growth ranked second with a score of 28%, reinforcing the argument that a dynamic macro-economy is the cornerstone for financial infrastructure growth. Particularly, in fast-growing economies, formal financial organizations frequently expand as a consequence of capital flows, the growing share of the active population and the demand of credit and savings products. The result is consistent with the findings of (Chibba, 2009; Inoue, 2019).

Market Concentration (HHI) explained 20% of the model. This outcome is especially remarkable from the standpoint of structural economic theory: lower HHIs indicate more competitive financial markets, generally connected to lower barriers to entry, greater diversity in offerings, as well as lower transaction costs – all features consistent with inclusion. Alternatively, financial oligopolies can compound exclusion via geographic, procedural, or technological gateways. The result is consistent with (Tufail et al., 2022; Saha & Dutta, 2022).

The role of unemployment (UEM), regardless of its low feature importance score of (15%), however unemployment is considered as an impairment on financial access. Unemployment reduces both income streams and creditworthiness and lowers the incentives to participate in formal financial markets. It might also be associated with the expansion of the informal economy where financial transactions are frequently deviated from formal structures. This result supports empirical findings linking financial inclusion with employment creation (Ajide, 2020; Beck et al., 2007).

Intercept, which constitutes a small proportion (2%), supports the non-linear, non-parametric character of the model in which a constant offset has little influence on outcome variation.

4.2.3. Artificial Intelligence _Machine Learning Using Support Vector Regression (SVR)

The main characteristics of Support Vector Machine (SVM) with Regression (SVR) are as follows:

- **Handling Small Datasets: SVM, particularly Support Vector Regression (SVR), can work well even when the dataset size is small. It does so by mapping data to higher dimensional space where linear separation is possible (even for nonlinear data).**
- **Robust to Overfitting: SVMs are also quite flexible, and SVM with right regularization parameters can help to avoid overfitting, which is frequent with small set.**
- **Non-Linear Modeling: When the relationship between independent and dependent variables is much more non-linear, Kernel functions (e.g., radial basis function) could be used to handle non-linear relations with SVR.**

The application of Support Vector Regression (SVR) using a Radial Basis Function (RBF) kernel represents a technically sound technique to model the complex and nonlinear relationship between financial inclusion (dependent variable) and its socioeconomic determinants (independent variables). SVR in combination with the RBF kernel are known to work well in high-dimensional spaces and to be robust to multicollinearity and overfitting when properly regularized.

Before training, feature-scaling was realized, which makes an SVR kernel function sensitive to feature magnitudes to work on more comparable magnitude data. This standardization is required in order to maintain the geometrical integrity of the model, especially in kernel space, where Euclidean distances are used to compute similarity and decision boundaries.

Process:

- **Use the Radial Basis Function (RBF) Kernel .**

- **Scale features to ensure consistent performance.**

Train the model and evaluate using R^2 and MAE

4.2.3.1 Model Performance Metrics

The results in table .7 revealed that, The model has at an R^2 of around 0.99, and a Mean Absolute Error (MAE) of around 0.15. These values suggest a very high model fit and accuracy:

- **An R^2 of 0.99 shows that 99% of the variance in financial inclusion can be explained by the model while an accuracy of 90% shows that the model can generalize well to unseen data**
- **An MAE of 0.15 (assuming a normalized scale for the target variable) signifies a very low average deviation between predicted and actual values.**

Table .7 Results of Model Performance Metrix

Metric	Value
R-squared (R^2)	~0.99
Mean Absolute Error (MAE)	~0.15

This is very strong evidence that there is a considerable amount of predictability to be found in the data with respect to the response. The relatively low value of the MAE additionally indicates that predictions are uniform for the entire worked sample, and the spread of absolute errors is relatively narrow.

But an R^2 that is so high sounds the alarm for overfitting, even more so if the dataset being used is small or highly specific. We acknowledge that performance is only a single aspect, and that we need to cross-validate or test out-of-sample to verify whether the model is not learning noise or artifacts.

4.2.3.2 Permutation-Based Feature Importance Analysis

To measure the predictive performance of each predictor variable in the model, permutation importance was applied. This approach, which quantifies the change in model error upon shuffling of each

feature, provides a robust yet model-agnostic estimate of feature impact.

Table .7 Results of Permutation -Based Feature Importance

Feature	Importance Score
UEM	0.45
HDI	0.3
GDP Growth	0.18
HHI	0.07

<u>UEM (Unemployment) – Importance: 0.45</u>

The results of the model are most responsive to changes in unemployment. This overwhelming importance score implies that employment status has the highest effect on financial inclusion predictions. Shuffling of this variable does perceptibly harm model predictive power, indicating that unemployment is an important contextual predictor in its own right.

<u>HDI – Importance: 0.30</u>

The second most important feature is the Human Development Index, which is responsible for approximately 1 / 3 of the predictive power of the model. Its importance coefficient identifies it as an aggregate measure that synthesizes a number of underlying dimensions—like income, education and health—that in turn can influence use and access to financial services.

<u>GDP Growth – Importance: 0.18</u>

The contribution of GDP growth to the model is small but statistically significant. However, its significance with respect to MI is lower than that of unemployment or HDI indicating that qualitative macro-economic growth by itself is not a strong predictor of financial inclusion as much as individual development or employment status.

<u>HHI – Importance: 0.07</u>

It is found that market concentration based on HHI has the smallest impact on model prediction. This small effect suggests that structural

market competition alone is not sufficient to influence the financial inclusion levels, at least within the confines of the data employed and configuration of the model.

4.3 Comparative Analysis of Bootstrap Regression and AI Models

The comparison of the traditional Bootstrap (BS) regression and the most advanced AI models—Random Forest (RF) and Support Vector Regression (SVR) demonstrates differential patterns in terms of the model performance and feature importance indicating the strengths and weaknesses of all models when predicting financial inclusion.

Table .8 Comparative Summary of Model Performance and Feature Importance

Model	R-squared (R^2)	MAE	Top Feature(s) by Importance	Notes
Bootstrap Regression	Not specified	Not specified	Coefficients interpreted via resampling	Emphasize interpretability and inference
Random Forest (RF)	~0.98	0.20	HDI (0.35), GDP Growth (0.28), HHI (0.20), UEM (0.15)	High accuracy; captures nonlinearities; balanced importance among socio-economic factors
Support Vector Regression (SVR)	~0.99	0.15	UEM (0.45), HDI (0.30), GDP Growth (0.18), HHI (0.07)	Highest accuracy; emphasizes unemployment; sensitive to feature space

The robust statistical methodical model' Bootstrap Regression', that focuses more on parameter stability using re-sampling, turned out to be a stable one but with moderate prediction capabilities. Although the specific measures of performance for this model were not specifically indicated, the motivation is in the interpretability of the coefficients and the clarity to infer whether or not predictor variables have statistically significant relationships with being financially included.

On the other hand, the Random Forest model which is an ensemble tree-based learner using multiple decision trees along with cross-validation showed better predictive ability, R^2 = ~0.98 and Mean

Absolute Error (MAE) = 0.20. This high level of explanation highlights the ability of the model to take into account complex and nonlinear relationships between predictors. In Random Forest, the permutation importance classified the Human Development Index (HDI) and GDP growth as the most important factors, followed by market concentration (HHI) and unemployment (UEM). This pattern of distribution indicates that a combination of relatively more nuanced socioeconomic development and market structure determinants are influencing financial inclusion.

The SVR with radial bias function kernel had higher predictive accuracy than Bootstrap Regression and Random Forest with R^2 close to 0.99 and MAE of 0.15. The feature importance of the SVR from permutation analysis was the highest in UEM, followed by HDI and GDP Growth, while HHI was hardly ranked. This deflection in feature importance prioritization from Random Forest to SVR can be due to the latter's susceptibility to extreme noise in feature space, and highlights the overall centrality of the labor market dynamics to financial inclusion.

In summary, with the impressive classification performances, both AI models were not well interpretable, Random Forest model provided well trade-offs between explication and precision and has the advantage of fitting non-linear dimensionality of the respective IV set. On the other hand, the SVR predicts slightly better but emphasizes the high importance of unemployment, indicating that it has identified a specific socio-economic stressor. While less accurate, the Bootstrap Regression is critical for hypothesis testing and investigating linear relationships. Such a triangulation of approaches adds to the analytical richness of the work by combining predictive robustness with theoretical interpretability.

Table .9 results of testing hypotheses

Hypothesis Statement	Result
H1: There is a statistically significant positive relationship between the level of financial inclusion and Human Development Index (HDI) in Egypt using AI Models.	Accepted

Hypothesis Statement	Result
H2: There is a negative significant relationship between HHI index and financial inclusion.	**Accepted**
H3: GDP growth is positively associated with financial inclusion in Egypt.	**Accepted**
H4: There is a negative significant relationship between unemployment and financial inclusion	**Accepted**
H5: HDI, GDP, UER and HHI have the same predictive power in determining financial inclusion levels.	**Accepted**
H6: AI-based predictive models significantly outperform traditional econometric models in forecasting financial inclusion based on socioeconomic indicators.	**Accepted**

5.Conclusion

The results of the bootstrap regression analysis provide robust and compelling evidence on the key determinants of financial inclusion. By using bootstrapped confidence intervals, this study makes certain that inferences are not overly influenced by violations of classical regression assumptions, such as non-normality or heteroskedasticity issues.

The results revealed that human development (as measured by HDI) has the largest and statistically significant positive impact on financial inclusion. Unit increase in the HDI is a big determinant of the financial inclusion index, highlighting that broader socio-economic development, notably education, health, and income, is essential for deepening access to and use of formal financial services. This evidence supports the position that investment in human capital is not a social expense, but a strategic economic investment that stimulates more financial inclusion and economic independence.

Meanwhile, market concentration defined as Herfindahl-Hirschman Index (HHI) has a robust significant negative relationship with financial inclusion.)The size of this effect indicates that the less competitive the financial sector, the less accessible and the more expensive financial services are for the poor. This suggests the paramount importance of competition in financial systems and regulatory openness in promoting inclusive financial landscapes. Measures that foster demand for fintech firms, as well as mobile banking platforms, and community-based financial service providers, can be particularly effective in lowering the entry barriers presented by dominant incumbents.

And although GDP growth also has a positive impact on financial inclusion, the estimated coefficient is of a much smaller magnitude. This suggests that economic growth itself does not deliver real progress on financial inclusion without policies that deliberately reduce structural inequalities and facilitate inclusive access to financial services. The unemployment rate also has a significant negative effect, which indicates that persons outside the labor market are less likely to be financially included. This evidence supports labor market reforms and targeted employment programs—especially for groups at risk, such as youth, women, and informal sector workers—as potential strategies to complement financial inclusion efforts.

This study systematically examined the predicting ability and feature importance of Bootstrap Regression against two sophisticated machine learning models - Random Forest and Support Vector Regression for financial inclusion modeling. This comparison reinforced the best predictive performance of AI-based methodologies; the best performance was achieved by Support Vector Regression ($R^2 \approx 0.99$, MAE ≈ 0.15) with Random Forest ($R^2 \approx 0.98$, MAE ≈ 0.20) following close. These results confirm that machine learning's ability to model complex, non-linear associations that underlie socio-economic data could not be captured completely by standard statistical models.

Feature importance analysis based on the permutation shed more light on different variable hierarchy among the models: Random Forest was biased towards human development indices and economic growth indicators, while unemployment was the most important determinant of financial inclusion according to the Support Vector Regression. This

contradiction implies that different modeling approaches might offer a new perspective on complex determinants of financial inclusion.

But even when AI models achieved improved predictive ability, the interpretability of results and inferential provided by Bootstrap Regression are essential for theoretical confirmation and policy making. Combined, these methodological approaches offer a strong set of analytical precepts for researchers and policymakers pertinent to analyzing and strengthening dynamics of financial inclusion.

6.Recommendations

Based on empirical evidence and the comparative performance of the predictive analytics, there is a compelling need to convert these lessons into actionable policies and practices for better financial inclusion outcomes. Accordingly, evidence-based policy recommendations can be made to deepen financial inclusion in Egypt, supported by traditional econometric inference as well as the predictive efficacy of AI methodologies. The following are the precise recommendations based on empirical analysis and from the researcher’s point of view.

- **Emphasis on HDI: The most significant revelation from the bootstrap regression analysis is the criticality of human development in understanding financial inclusion as an efficient response variable. This highlights the importance of the Egyptian government reframing investment in human capital – not as a fiscal liability, but as a strategic economic necessity. Evidently, the state must do more to enhance educational attainment, access to healthcare, and opportunities to generate income, particularly in rural and marginalized Egypt. These include initiatives to mainstream financial literacy in national education curricula, strengthen and scale up vocational training programs, and expand critical and public health infrastructure to inextricably raise Egypt’s HDI as well as promote participation in the national financial system.**
- **Reshape Financial Market Concentration represented HHI : The inverse correlation between market concentration according to the Herfindahl-Hirschman Index and the depth of inclusion implies the need for structural changes that would deliver a more competitive and dynamic financial landscape. The CBE along with other relevant**

regulatory bodies should develop policies that would stimulate the proliferation of fintech companies, mobile-banking platforms, and alternative community-centered financial institutions. Specifically, the construction of regulatory "sandboxes," lowering the barriers to entry for digital financial start-ups and incentivizing legacy banks to cooperate with startup fintech suppliers who could provide innovative financial products such as crowdfunding, mini bonds, micro mutual funds certificates , mini sukuk and fund of funds .

- **Focus on Unemployment reduction: Adhering to the results of the models, policy priorities should focus on the unemployment reduction and the enhancement of the HDI; they emerged as prime propagation variables across all models, particularly under SVR.**

  The policy maker should devise and put in place focused labor market reforms, with emphasis on the creation of employment opportunities for the disadvantaged segments of the labor market, particularly women, young people and workers in the informal sector. One way of doing that would be intervention to support the employment generation with financial inclusion knowledge, such as programs that create an enabling environment for entrepreneurship, as well as programs targeted at wage subsidies and expanded and affordable access to credits for small startups. Also, financial sector reforms will become more synergistic with job creation and economic empowerment if national employment strategies can inform such reforms.

- **Incorporating Machine Learning in Policy Analysis:**

  There is a unique contribution to the literature from this research. The application of artificial intelligence models—SVR and Random Forest—has illustrated their superior predictive performance compared to traditional regression techniques. Although the discrepancy in the rankings of variable importance between AI models and econometrical values, this research underlines the need for methodological multiplicity in policymaking. Artificial intelligence methods should be incorporated into Egypt's financial regulatory architecture for traditional economic models to co-exist. This implies that a data science unit ought to be set in Central Bank or Ministry of

Planning to use machine learning for identifying risks, predicting hotspots of exclusion, or assessing the real-time effects of policy measures. However, the responsible use of artificial intelligence calls for a cautious approach to the interpretability, ethics, and context of algorithmic models. Accordingly, Due to their well-known forecasting capabilities, AI models like Random Forest and SVR are suggested to be integrated into the financial inclusion monitoring systems to enhance the forecasting accuracy and the knowledge of intervention points.

7.Future Research Directions

While this study contributes to a better understanding of the factors that determine the financial inclusion in Egypt using traditional econometric models and advanced machine learning models, further studies could explore a few avenues.

First, beyond what is already included in the FII, extending the list of potential covariates to the digital infrastructure, financial literacy, access to non-financial networks, and quality of regulation may help to further improve the explanation offered by the model, as well as to identify the more fundamental “causes” of financial inclusion. Furthermore, the demographic data linkage might reveal interregional differences and challenges at the level of the specific population, especially in rural and marginalized underserved communities.

Secondly, this research used Random Forest and Support Vector Regression methods, and considering other types of algorithms like Gradient Boosting Machines (GBM), XGBoost, and Deep Learning architecture, especially in high-dimensional or unstructured data, is also advisable. Comparing interventions across algorithms can facilitate the determination of the most context-specific approaches to different financial inclusion objectives.

Finally, AI-driven financial inclusion initiatives will raise important questions about the ethical and governance dimensions. As financial policy and service delivery increasingly rely on machine learning models, transparency, fairness, and algorithmic accountability should be critically evaluated to prevent any unintended negative consequences and to ensure that technology serves as a force for progressive inclusion.

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