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Impact of AI Transformation, Financial Inclusion, and Operational Efficiency on Global Economic Growth: Dynamic GMM Approach

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ABSTRACT: Using system Generalized Method of Moments (GMM) estimation, this study examines how AI adoption, financial inclusion, and operational efficiency affect GDP growth across 89 countries, for the period 2018 - 2023. The results show that GDP growth is positively affected by AI adoption, financial inclusion, quality of governance, and education. Conversely, operational efficiency and systemic financial risk show a negative correlation with economic performance, contrary to common assumption characterizations. These results are robust to a difference GMM approach; additionally, it is revealed that inflation, interest rates and R and D expenditure are bad for GDP indicating that macroeconomic instability, high borrowing cost and inefficient innovation investment hinders growth. Policymakers should promote AI adoption, financial inclusion, good governance, and education while mitigating financial risks, controlling inflation and interest rates, enhancing operational efficiency, and ensuring effective R&D investment to sustain GDP growth and economic stability.

Keywords: AI adoption, financial inclusion, operational efficiency, GDP growth, dynamic GMM. JEL: O33, G21, E44, O11, E61

I. INTRODUCTION

The rapid advancement of artificial intelligence (AI) technologies is revolutionizing industries and economies worldwide. Within the financial sector, AI transformation has emerged as a critical driver of innovation, operational efficiency, and accessibility. The term "AI transformation" is often used to describe the comprehensive integration of artificial intelligence into various aspects of business operations, products, and services, aiming to drive innovation, efficiency, and growth. For instance, [1] defines AI transformation as a strategic initiative where businesses adopt and integrate AI to enhance their operations and offerings. Even though its transformative potential is enormous, the impact of AI on macro-economic outcomes, in particular GDP growth, is underexamined. At the same time, the importance of financial inclusion, a known driver of economic participation, has risen to the top of global development agendas. Yet, this area of research remains largely unexplored concerning the relationship between AI adoption, financial inclusion, operational efficiency, and their augmentative effects on economic growth across diverse economic contexts. Whereas the global economy is still struggling with inequalities and systemic risks, it is critical for us to understand the relevance of these drivers for improving inclusive and sustainable growth.

Although a considerable amount of literature exists on how technology and financial systems contribute to economic growth, huge challenges remain. One is that the adoption of AI has occurred unevenly between countries, with these technologies possibly benefiting primarily wealthier economies and low- and middle-income countries becoming sequestered from their benefits [2]. Faced with challenges at home, such a scenario raises alarm bells about a potential widening of global economic inequities as A.I. turbocharges the productive and innovative capacities of wealthier economies, while fizzling in others that lack advanced technological muscle. Second, although the effectiveness of financial inclusion in empowering underserved populations and reducing poverty has been demonstrated [3] scalability and the use of emerging technologies in financial inclusion has been limited. Third, operational efficiency is a key driver of financial institutions' capacity to support economic growth but is under-explored in the context of AI-driven transformations. All things considered, such challenges highlight the need to examine the interlink of synergies between AI adoption, financial inclusion, and operational efficiency as a possible route towards equitable economic growth.

Addressing these gaps is essential as policymakers seek to align technological advancements with broader economic and social goals. Failure to do so risks deepening in-equalities and undermining the potential benefits of AI for global economic development. The primary objective of this study is to analyze the combined effects of AI adoption, financial inclusion, and operational efficiency on GDP growth in a diverse set of 89 countries between 2018 and 2023. The importance of this research is in its integrative approach to a macroeconomic understanding of the impacts of AI adoption, financial inclusion, and operational efficiency. In contrast to previous studies, which largely examine these variables in isolation or within more geographically constrained groups, this study takes a global view, encompassing data from a wide range of countries. The study provides a comprehensive view of how these relationships play out in shaping GDP growth, with its inclusion of countries from all parts of the world and income classifications from high income economies such as the United States and Germany, to emerging markets such as India and Kenya.

Although artificial intelligence (AI) has become a major focus of economic and technological research, most existing studies examine its impact in isolation typically within high-income economies or specific sectors such as manufacturing or healthcare [4, 5]. Similarly, while financial inclusion and operational efficiency have each been associated with economic development [6, 7], their interaction with AI adoption and their combined influence on GDP growth remain underexplored. Furthermore, much of the literature focuses on developed regions, thereby overlooking lower-income and emerging markets where digital infrastructure and financial systems are still evolving [8, 9]. This fragmented treatment of the three dimensions AI, financial inclusion, and institutional efficiency highlights a significant theoretical and empirical gap.

This study contributes to bridging that gap by adopting an integrative and global approach. It examines the combined effects of AI adoption, financial inclusion, and operational efficiency on GDP growth across 89 countries from 2018 to 2023, encompassing both advanced and developing economies. This multidimensional analysis is further strengthened by the use of the Generalized Method of Moments (GMM), a robust econometric technique that addresses potential endogeneity issues often neglected in cross-country macroeconomic research [10, 11]. By moving beyond the traditional siloed frameworks, the study offers a novel conceptual model that connects technological advancement with financial systems and institutional performance to provide a more complete understanding of their macroeconomic implications.

The rationale for this research is underscored by the rapid acceleration of AI technologies and their uneven diffusion across global economies. While AI presents new opportunities for innovation, productivity, and governance, the benefits are not uniformly accessible particularly in regions with underdeveloped financial and institutional systems [12, 13]. This study is therefore timely and essential, as it contributes both theoretically by proposing a new integrative framework and empirically by offering cross-country evidence using rigorous methodology. The findings have important policy implications, suggesting that targeted investments in AI infrastructure, financial inclusion initiatives, and institutional efficiency reforms are critical to ensuring inclusive and sustainable economic growth in the digital era.

II.THEORETICAL REVIEW

1. ENDOGENOUS GROWTH THEORY

The Endogenous Growth Theory claims that long-run economic growth is not determined by an external force but, instead, by factors such as innovation and human capital [14]. In line with AI adoption, a theory this well aligns with the role of AI acting as a catalyst for generating a lot more productivity and efficiency in all the sectors in an economy. Furthermore, AI technologies offer the potential for financial inclusiveness, making operations and transaction costs more manageable for financial institutions, which in turn could increase GDP growth. As such, the study contributes to the hypothesis that innovation driven by artificial intelligence enhances economic growth, especially gravitating toward those economies that are closely rooted with technology within the business as well as financial cycle.

2. TECHNOLOGY ACCEPTANCE MODEL (TAM)

The Technology Acceptance Model (TAM) describes how perceived usefulness and ease of use influences the adoption of new technology by either individuals or organizations [15]. Specifically in this study, the umbrella of the impact of AI technology on financial institutions covers their implications to problems of financial inclusion and operational efficiency. Firms have a greater chance of adopting AI to improve access to underrepresented populations in capital if they not only see value but use that value to develop financial services, risk mitigation and customer contact through automation. This resonates with the study's investigation on how the adoption of AI will fuel financial inclusion and spur overall GDP growth through increased participation in the economy.

3. FINANCIAL INTERMEDIATION THEORY

The Financial Intermediation Theory by Schumpeter emphasizes the significance of financial institutions in economic development by channeling resources to productive sectors of the economy [16]. AI improves financial services, including credit evaluations, fraud prevention, and risk assessment, resulting in greater inclusivity and lower costs. Finance inclusion through AI technology adoption allows an increase of GDP as wide-spread economic activity, capital investment, and entrepreneurship contribute to growth. AI is part of financial services as a financial intermediary, which itself promotes eco-nomic growth.

III. EMPIRICAL REVIEW

The most widely recognized measures of economic progress and development in a nation are economic growth, as measured by annualized growth in GDP. Growth rate of GDP measures the total amount of economic activity (production, consumption, and investment in the country) and the extent of policies implemented to improve such activities [17, 18]. However, GDP growth as a metric has been criticized for not considering income inequality, environmentally unsustainable production, and social well-being [19]. Despite these drawbacks, GDP growth is a critical measure because it remains closely correlational with technological progress, financial soundness and human capital development [20]. Even as a dependent variable, GDP growth has been studied by macro-economists seeking to understand the evolution of structural reforms, innovation and countries' financial systems.

On a global scale, adoption of AI is transforming industries, the most significant benefactors being those in the financial sector. The adult use of AI involves the addition of analytics, risk assessment, decision making capabilities in financial products which improve innovation and efficiency [21]. But we have machine learning algorithms that help in prediction modeling as well as fraud detection and AI chatbots that improve customer engagement that can lead to better delivery of financial services [22, 23]. These embraces of AI also stimulated the economies, it was found that economies that adopt way more AI additionally grow quicker, by greater than innovation multiplier impacts on productivity and market growth [24, 25]. However, there are those who propose that the economic advantages of AI are not fairly shared, disproportionately benefiting developed nations with sophisticated technological infrastructure. Additionally, AI-driven job displacement and ethical issues like algorithmic bias are also increasingly worrying about potential sources of social inequities [26] We can see the great transformation power of AI in solving operational inefficiency and market uncertainty, such positive factors make AI a key driver of economic growth despite the above challenges.

While financial inclusion is increasingly recognized as a driver of economic development, since it provides access to basic financial services such as credit, savings, and insurance. Financial Inclusion helps in economic participation, alleviating poverty and improving entrepreneurship [27]. Having access to financial services enables the un-banked, predominantly in emerging market economies, to save, invest and manage against risks of more financial inclusive populations are by definition more economically resilient.

Yet digital gaps and absence of financial literacy pose major challenges to attaining financial inclusion in the third world. AI in Financial Services In this environment, digital financial services powered by AI, including mobile banking and fintech platforms, help bridge the gap by offering financial solutions that are affordable and accessible [28, 29]. These innovations have shown much advancement, but the excessive dependence on digital platforms comes with challenges in data privacy, cybersecurity, and regulatory over-sight [30] Additionally, operational efficiency is also key to economic stability and growth in the financial sector. Operational efficiency indicates financial institutions' capacity to curb costs while increasing output, as measured by data such as the cost-to-income ratio [31]. Increased efficiency leads to lower service costs, higher profitability and greater resilience in the face of economic shocks for financial institutions. Moreover, operational efficiency is enhanced by automation, which is possible due to AI technologies that auto-mate mundane tasks, minimize errors, and facilitate real-time analytics [32-34]. Despite all such advancements, the system is hard to be efficient due to structural inefficiencies, regulations, and the costs of provisioning and operationalization of AI. Besides enhancing competitiveness, efficiency gains can also exercise downward pressure on employment and real wages and this has social and political ramifications as well. This means that the economic benefits of operational effectiveness need to be looked at in addition to their broader social impact.

It is the synergy between these three factors towards AI adoption, inclusion, and efficiency (operational) that positively contributes towards growth in these three areas. These AI technologies allow financial institutions to book customers who would otherwise re-main unbanked, hence advancing greater financial inclusion. At the same time, automation powered by AI improves operational efficiency, lowering costs and optimizing re-source allocation, setting off a cascading effect that elevates GDP growth [35]. However, the literature suggests there are marked gaps in uptake of AI and its benefits, generally skewed toward rich nations with advanced tech ecosystems. Low-income countries have infrastructure deficits, limited digital literacy, and regulatory gaps that make it challenging to scale AI solutions [36]. Systemic risks related to the rapid adoption of generative AI including speculative bubbles, unfair market competition, and cybersecurity risks further imply the need for appropriate policies to provide safeguards against the harm that might arise [37-39].

The economic impact of artificial intelligence (AI) has gained significant academic attention over the past decade, especially in the context of productivity, innovation, and structural transformation. [4] argue that AI technologies represent a “second machine age,” potentially driving exponential productivity growth. Similarly, [40] provide evidence that AI and automation have dual effects on labor productivity and employment: while they increase firm-level efficiency and innovation, they can also suppress wages and displace routine jobs. At the macroeconomic level, [5] found that AI-adopting countries enjoy enhanced research productivity and innovation spillovers, suggesting a long-run positive effect on GDP. However, these benefits tend to be concentrated in advanced economies with mature digital ecosystems, leading to increasing disparities across regions [41, 12].

In terms of AI and GDP growth, empirical studies are beginning to demonstrate more definitive links. For instance, [42] found that AI could contribute up to 1.2% additional GDP growth annually in developed countries by 2030, largely driven by automation, customer service enhancement, and analytics-driven decision-making. However, the same study cautions that such benefits are unevenly distributed and depend on complementary investments in human capital and digital infrastructure. More recent evidence from [8] reports that in countries with well-integrated digital finance systems, AI-driven fintech applications have positively influenced national GDP growth rates through improved credit allocation and reduced transaction costs. However, concerns persist regarding job polarization, regulatory lag, and algorithmic bias—issues that may ultimately offset or complicate AI's contribution to inclusive growth [13, 44].

Financial inclusion, defined as the accessibility and usage of formal financial services by underserved populations, has long been associated with economic growth, poverty reduction, and entrepreneurship. Using data from over 140 countries by [7], show that access to credit, savings, and insurance correlates with increased household resilience and higher rates of small business formation. Financial inclusion supports broader economic participation, particularly in emerging markets. Yet, digital divides, low trust in financial institutions, and weak consumer protection frameworks limit its effectiveness. The rise of AI-powered digital financial services—including robo-advisors, mobile banking, and algorithmic credit scoring has the potential to overcome these barriers. Study [13] argue that AI can enhance inclusion by reducing operational costs and expanding the reach of financial products, particularly in remote or underserved areas. Nonetheless, AI-based systems also present new challenges such as data privacy concerns, exclusion due to algorithmic bias, and over-reliance on black-box models that regulators struggle to audit.

Operational efficiency, particularly in the financial services sector, is often measured by cost-to-income ratios and return on assets. The literature typically links higher efficiency to improved competitiveness, service quality, and profitability [45, 46]. AI-driven automation such as robotic process automation (RPA), predictive analytics, and algorithmic trading has enhanced back-office functions and risk assessment capabilities, improving overall performance. For instance, [47] note that AI has significantly reduced processing times and operational overheads in banks and insurance firms. However, a noteworthy paradox in the literature concerns the inverse relationship between efficiency and broader economic growth. Study [48] suggest that hyper-efficiency achieved via automation can lead to job losses and wage stagnation, which may suppress aggregate demand and reduce GDP growth in the long run. Similarly, [49] argues that while AI improves firm-level performance, it does not guarantee widespread economic prosperity unless accompanied by inclusive labor and education policies.

IV. HYPOTHESIS DEVELOPMENT

1. AI ADOPTION AND GDP GROWTH

AI is rapidly transforming financial systems through un-precedented productivity, efficiency, and innovation. AI-powered automation improves decision-making systems, brings optimal resource allocation, and relaxes transaction cost margins, which leads to better economic performance [50]. From faster data processing to predictive analytics and risk assessment, AI transforms financial services while creating opportunities for more efficient markets and sustainable economic growth [51]. In addition, AI also drives financial inclusion by enhancing availability to digital banking, automated lending as well as investment advisory services, and thus stimulates eco-nomic activities [52]. Nevertheless, the effects of AI on GDP growth are heterogeneous across economies and are contingent upon variables like technological preparedness, regulatory environments, and labor market adjustments [53]. Although these dimensions of AI adoption can stimulate economic growth in high technology penetration subnational regions in high income economies, they can also prove to be negative factors in economies with insufficient technology infrastructure and stringent regulations. Moreover, policy implications are needed for job displacement caused by increased automation and inequality from unequal access to cutting-edge developments in AI technology [54]. From this perspective, the hypothesis below is:
H1: AI adoption has a significant positive impact on GDP growth.

2. FINANCIAL INCLUSION AND GDP GROWTH

Financial inclusion significantly contributes to economic growth by providing access to financial services, credit, and investment opportunities. Financial inclusion helps in creating a conducive environment for entrepreneurship, savings and efficiency, which ultimately has impact on the productivity and economic participation of the people [55] through integrating people from the underserved segments of society to be an active part of the formal financial system. In addition, providing access to banking, digital payment systems, and microfinance institutions can also reduce income inequality, promote financial stability, and support sustainable economic development [56]. The contribution of financial inclusion to better financial resilience derives from the fact that access to financial products and services helps incorporate individuals and small businesses into the process of risk management, investment in productive activities in the economy and wealth accumulation over time [57]. But its role in GDP growth also depends on how efficient financial institutions are and how strict the regulatory regime is. In economies suffering from weak financial infrastructure or governance, greater access to finance does not necessarily imply productive investments and may instead lead to financial instability or resources being misallocated [58]. Consequently, although financial inclusion is a pro-found driving force for economic growth, its impact is dependent on the wider economic and institutional environment. For this reason, the following hypothesis is:
H2: Financial inclusion has a significant positive impact on GDP growth.

3. OPERATIONAL EFFICIENCY AND GDP GROWTH

Operational efficiency, as measured by the cost-to-income ratio, reflects the degree with which financial systems turn input into productive financial services [59]. By promoting a more efficient level of banking, banks and other financial institutions can lend at lower costs, inhibit financial constraints on firms, and allow capital to form, thus promoting business growth and general productivity in the economy [60]. It improves risk management and decreases credit allocation inefficiencies and also encourages investments in high-growth areas; hence, an efficient financial institution leads to economic stability [61]. When the pressure to optimize operational costs is excessive, innovation stagnates, services worsen, and contributions by the financial sector to other economic activities are constrained [62]. The critical perspectives on the role of cost-effectiveness, as applied to economic growth, therefore imply that operational efficiency can either serve or jeopardize growth outcomes, in tandem with structure and incentives particularly in the financial intermediation realm. The following hypothesis is due to this reason:
H3: Operational efficiency has a positive significant impact on GDP growth.

V.METHODOLOGY AND DATA SOURCE

Using a GMM panel technique this study analyzes the combined effects of AI adoption, financial inclusion, and operational efficiency on GDP growth in a diverse set of 89 countries between 2018 and 2023. Figure 1 shows the research framework of the study.

For this the data is gathered from credible and standardized data sources. Data for the dependent variable, GDP growth rate, was collected from the World Bank and International Monetary Fund (IMF) databases. This data presents the annual GDP growth percentages of countries. Independent variables are taken from many international financial and economic databases. AI_ADOPT: AI adoption represented by an AI index (from 0 (low adoption) to 1 (maximum)) based on AI research articles and global AI preparedness indices. FIN_INCL financial inclusion, measured as the World Bank's Financial Inclusion Index, which ranges from 0 to 100, measuring access to financial service. Operational efficiency (EFFICIENCY): cost-to-income ratio from financial reports of banks and institutions from World Bank and BIS financial datasets. Control Variables are taken from relevant global economic indicator. For GOV_QUAL, we use the World Governance Indicators (WGI), which measure the effectiveness of institutions on a scale ranging from -2.5 to 2.5. SYS_RISK captures systemic risk from IMF Global Financial

Stability Report (a measure of financial system stability). Finally, we measure education level (EDU) by the average years of schooling according to the World Bank's Human Development Indicators.

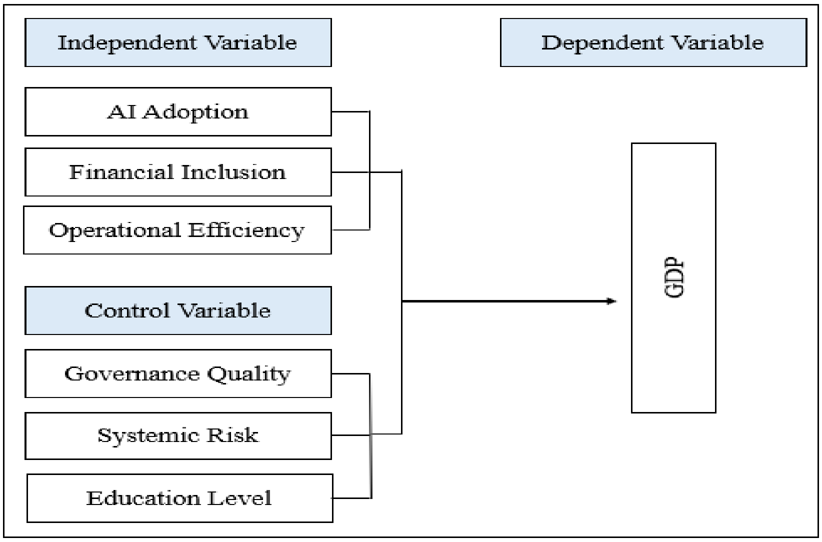

FIGURE 1. Research framework.

1. DEPENDENT VARIABLE

The study uses GDP growth as a dependent variable, which is measured as an annual percentage change in the gross domestic product (GDP) of each country. The economic growth or decrease in GDP is as important as the total economic growth which can be seen in [63] as it shows what is the state of a country in terms of GDP. Moreover, the recently well-known GDP growth in the macroeconomics literature captures the overall impact on economic growth of production efficiency, technological innovation, and access to finance [19].

2. INDEPENDENT VARIABLES

This study has three independent variables. To this end, we examine the relationships between artificial intelligence (AI_ADOPT), financial inclusion (FIN_INCL), and operational efficiency (EFFICIENCY) and their impact on seeding GDP growth. AI_ADOPT is the AI index (0 to 1) as a measure of AI adoption in financial products. Higher figures denote a higher degree of adoption of AI-driven technologies, including machine learning and predictive analytics, in financial services. Such technologies improve decision-making, automate many of the processes, and optimize resource allocation leading to a more efficient financial sector that fuels more economic growth [64]. The domain of AI adoption is particularly transformational in 3 areas, innovation, customer experience enhancement and uplifting financial institution's responsiveness to market dynamics [65].

Financial inclusion, quantified through the World Bank's Financial Inclusion Index (0–100 scale), symbolizes access to basic financial services including credit, savings, and insurance. Higher financial inclusion encourages economic participation because it helps individuals and businesses to be empowered, promotes entrepreneurship, and enhances consumer spending, with these activities contributing to GDP growth [66]. EFFICIENCY: Cost-to-income ratio (in percentage, higher is worse) measures how well financial institutions follow operational performance. Higher efficiency– as implied by a lower ratio– allows institutions to offer affordable and reliable services that enhance economic stability. Specifically, AI adoption drives financial inclusion and operational efficiency by eliminating geographical and structural barriers, mechanizing processes, and improving operational costs, thus leading to better economic performance [67]. Table 1 describes the variables.

Table 1. Variable description.

Category	Variable	Measurement	Expected Result
Dependent variables	GDP	Annual GDP growth rate (%) for each country	?
Independent variables	AI_ADOPT	AI Adoption: A proxy measure of AI adoption in financial products (AI index, scaled between 0 and 1).	-/+
	FIN_INCL	Financial Inclusion: Index measuring access to financial services (World Bank's Financial Inclusion Index, scaled between 0 and 100).	-/+
	EFFICIENCY	Operational Efficiency: An indicator of financial institutions' operational efficiency (cost-to-income ratio, expressed as a percentage).	-/+
Control variables	GOV_QUAL	Governance Quality: Governance index measuring institutional quality (World Governance Indicators, scaled between -2.5 and 2.5).	-/+
	SYS_RISK	Systemic Risk: A measure of financial system stability (systemic risk indicator, scaled between 0 and 1).	-/+
	EDU	Education Level: Average years of schooling.	-/+

5.3 CONTROL VARIABLES

Three control variables were integrated into this research to cover all hidden factors that could affect the GDP growth explanation. They are quality of governance (GOV_QUAL), systemic risk (SYS_RISK) and the educational level (EDU). These control variables are indicators of governance quality, financial system stability, and levels of education, all of which are important drivers of economic performance. GOV_QUAL This variable is the governance quality; it is measured using the World Governance Indicators (WGI) index; this index is scaled between -2.5 (weak governance) and 2.5 (strong governance). The quality of governance, which includes the effectiveness of institutions, the rule of law, and political stability, as well as regulatory quality can affect the economic growth potential of a country [28]. Better governance increases investor confidence, improves re-source allocation and reinforces contract enforcement, all of which creates a conducive environment to achieve sustainable growth.

SYS_RISK reflects systemic risk (financial system stability) aggregated on a scale of 0 (low risk) to 1 (high risk) Higher systemic risks may disrupt financial markets, restrict its credit market, and lower its overall economic performance. SYS_RISK is included as a control variable to ensure that the analysis is adjusted for swings in financial stability that may otherwise distort the results [68]. The last one, EDU, calculated as the average years of schooling, refers to the educational attainment of a country´s population. More significant education levels increase labour production, enhance innovation, and encourage economic growth [69]. The study also controls the impact of governance, financial stability and education on GDP growth, ensuring the independent assessment of the effects of AI adoption, financial inclusion and operational efficiency.

5.4 MODEL SPECIFICATION AND ANALYTICAL TECHNIQUES

The study aims to evaluate the economic effects that arise from these contributing factors of AI adoption, Financial Inclusion and Operational Efficiency on GDP based on 89 worldwide and thoroughly sampled per 2018-HP, respective We expose scope between 2018 and 2023. Several interesting criteria for selecting the countries for this study have been taken into consideration. This increases the generalizability of the findings by selecting a diverse group of countries, such as those from Africa, Asia, Europe, the Americas, and Oceania. You're also trained in economic diversity, such as low-income, middle-income, and high-income countries as defined by the World Bank. This makes it possible to compare economic growth and technological uptake across income levels. Furthermore, countries have been chosen for their relevance to the focus of the study on AI adoption, financial inclusion, and operational efficiency; prioritizing countries that have varying degrees of involvement in technology-driven financial products and varying levels of Financial Inclusion. The other important selection criteria are data availability, which can provide reliable and consistent data on the key variables of interest (such as economic growth, AI adoption, financial inclusion and systemic risk) for the period under study (which is 2018–2023). Finally, countries with significant stakes in global and regional markets (e.g. U.S. and China, Germany) and emerging economies (e.g. India, Brazil, Kenya) are included in the sample, giving a balanced view on the role played by AI adoption and financial inclusion in global economic growth.

In order to address potential endogeneity concerns and ensure robustness of results, the Generalized Method of Moments (GMM) estimation technique is employed in our study. Specifically, to deal with the within-differences of the variables, we apply the system GMM estimator, which can control problems that are not solved by the conventional panel estimators, such as Ordinary Least Squares (OLS), Random Effects (RE) and Fixed Effects (FE) [30]. To ensure the robustness of the results obtained by this study, the difference GMM method uses the inclusion of additional macroeconomic variable inflation rate (INF_RATE), financial market variable interest rate (INT_RATE) and technological and innovation variable research and development expenditure (RD_EXP). But these extra variables at least help control for those outside factors that might affect GDP growth. If the original results still hold under the introduction of these variables, it further supports the idea that AI adoption, financial inclusion, operational efficiency, governance quality, education, and systemic risk have true impacts on economic growth.

The first difference GMM estimator developed by [70] employs the first differences of the variables to remove unobserved time-invariant heterogeneity, enabling us to reduce potential biases from omitted variables. One common instrument in the literature is to use lagged versions of dependent and independent variables. Specifically, by differencing the variables to isolate the variation between individuals, it corrects for biases that can arise from these common problems, including, but not limited to, autocorrelation, and heteroscedasticity [70]. We use the difference GMM because it complements the system GMM estimator. System GMM augments the efficiency of moment conditions by combining level and difference equations, while the difference GMM estimator internalizes first differences only, which allows for a tighter control for unobserved heterogeneity, serving both as a robustness check on the instrument's validity [71]. Combining these approaches is viewed as logical, likely increasing the robustness of results, especially when the dependent variable is persistent (as is typically the case with measures of financial performance) [72]. The addition of difference GMM also adds further robustness to the output, free from dynamic panel biases. The baseline model of the study is as follows:

$$GDPitc = \alpha 0 + \beta 1 AI\_ADOPTIONitc - 1 + \beta 2 FIN\_INCLitc + \beta 3\, EFFICIENCYitc + \beta 4\, GOV\_QUALitc + \beta 5\, SYS\_RISKitc + \beta 6\, EDUitc + \varepsilon itc \tag{1}$$

In the above models, $\alpha 0$ stands for intercept, i represents the firm, t stands for the time, c stands for the country. GDP_{itc-1} is the one period lagged for the dependent variable. ε indicates the error term in the models. Estimation based on the model may encounter three sources of endogeneity: simultaneity, arising when the independent variables operate both as functions and as the expected values of the dependent variable; unobservable heterogeneity, where factors not directly observable are influenced by both the dependent and explanatory variables. Measurement error occurs when there are inaccuracies in the measurement of variables, which can bias the estimated relationships in the model. To address these challenges, the GMM estimator is employed, following the approach outlined by [71]. This choice finds support in the work of [73], who postulated that GMM exhibits the most robust correction impact on coefficients.

VI. RESULTS AND DISCUSSION

The descriptive statistics in Table 2 show that the average GDP growth rate is 7.942%, with a standard deviation of 2.114%, indicating moderate variation across countries. GDP growth ranges from 2.452% to 13.782%, highlighting significant disparities in economic performance. AI adoption has a mean value of

0.554, with values ranging between 0.204 and 0.900, and a low standard deviation (0.210), suggesting that AI adoption is relatively consistent across the observations. Financial inclusion, on the other hand, shows considerable variability, with an average score of 59.02, a standard deviation of 17.186, and values ranging from 30.278 to 89.876, indicating that access to financial services varies greatly among countries.

Table 2. Descriptive statistics.

Variable	Obs.	Mean	Std. Dev.	Min	Max
GDP GROWTH	534	7.942	2.114	2.452	13.782
AI ADOPT	534	.554	.21	.204	.9
FIN INCL	534	59.02	17.186	30.278	89.876
EFFICIENCY	534	55.254	14.625	30.247	79.971
GOV QUAL	534	.761	1.016	-.989	2.494
SYS RISK	534	.398	.171	.1	.699
EDU	534	10.496	3.212	5	15.943

Furthermore, efficiency and government quality also display notable differences across observations. Efficiency has a mean of 55.254, with a standard deviation of 14.625, and ranges from 30.247 to 79.971, reflecting moderate disparities in institutional or operational performance. Government quality averages 0.761, with significant variation (standard deviation of 1.016) and scores ranging from -0.989 to 2.494. Systemic risk is relatively contained, with an average of 0.398 and a narrow range of 0.100 to 0.699, indicating less variation across countries. Education shows moderate variability, with a mean of 10.496, a standard deviation of 3.212, and a range from 5 to 15.943, highlighting differences in educational attainment levels.

Table 3 shows the result of correlation analysis which reveals that most variables exhibit weak or negligible linear relationships with each other. AI adoption (AI_ADOPT) has a very weak positive correlation with systemic risk (SYS_RISK) (0.049) and education (EDU) (0.042), while its relationship with financial inclusion (FIN_INCL) (0.032) and efficiency (EFFICIENCY) (0.011) is minimal, suggesting that AI adoption is largely independent of these factors. Financial inclusion (FIN_INCL) shows a weak positive correlation with education (EDU) (0.069) and marginal associations with efficiency (EFFICIEN-CY) (0.023) and government quality (GOV_QUAL) (0.037), indicating that higher financial inclusion is slightly associated with better governance and education levels. Meanwhile, government quality (GOV_QUAL) and efficiency (EFFICIENCY) have negligible correlations with most variables, reflecting minimal interdependencies.

Table 3. Matrix of correlations.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
AI_ADOPT	1.000					
FIN_INCL	0.032	1.000				
EFFICIENCY	0.011	0.023	1.000			
GOV_QUAL	-0.021	0.037	0.014	1.000		
SYS_RISK	0.049	0.001	0.023	-0.000	1.000	
EDU	0.042	0.069	-0.038	0.004	-0.032	1.000

The results from the GMM analysis in Table 4 indicate that AI adoption (AI_ADOPT) and financial inclusion (FIN_INCL) positively impact GDP growth (GDP_GROWTH). These results are consistent with existing literature that shows that the increased availability of technology and financial resources leads to economic growth. Integrating AI is believed to stimulate productivity, efficiency, and innovation, which enhances economic output [15], at least as far into the future as October 2023. AI also beneficial for business practices and cost saving increase competitiveness and boost growth in GDP [16]. This means that financial inclusion is related with greater access to credit, increase in entrepreneurship, greater investment in human capital which leads to economic growth [21]. In countries where the financial system works well, economic performance is stronger as the financial services allow economic resources to engage in economic activity effectively [22].

While the correlation analysis indicates that AI adoption and financial inclusion have positive effects on GDP growth, the weak or negligible correlations imply limited direct linear relationships between these variables and GDP growth. This means that their effects may have a more nuanced impact and be mediated by other factors like institutional quality, infrastructure, and the skill level of the labor force. Further, the use of the GMM approach corrects for endogeneity meaning that the positive effects observed are likely robust to reverse causality concerns. Therefore, although AI usage and increased instances of financial inclusion are good for economic development, their effect may vary based on additional determinants like governance, human capital, and innovation environments. Efficiency has a negative relationship with GDP growth (GDP_GROWTH), which means that increasing efficiency leads to a reduction of GDP growth. More efficiency in resource allocation, production, and governance has been traditionally anticipated to improve economic growth [33]. In certain cases, structured changes, fiscal repression, or even inflexible labor markets may also be less synonymous with efficiency than short term economic maintenance.

This phenomenon could potentially be explained by the fact that most of the times efficiency improves at the cost of downsizing, labour saving technology, and cuts in government spending negatively influencing aggregate demand and GDP growth in the short run [57]. In emerging economies, attention to efficiency-based austerity programs risk lower government investment, as a percentage of GDP, in crucial sectors like infrastructure, education and social programs with potentially negative impact on long-term growth potential [35]. And if, instead, the source of efficiency gains are the pockets of sectors that do not have the economic spillover effects, financial efficiency or administrative productivity as opposed to industrial productivity over everything, their overall contribution to GDP growth would be limited [36]. Furthermore, excessive focus on efficiency in some economies might also crowd out innovation and risk-taking, which are key drivers of sustainable growth. The search for savings may disincentivize firms and governments to invest in new technologies and workforce development, suppressing growth [37]. So, while efficiency is almost always a good thing, its negative impact on GDP growth in this study may simply be a symptom of short-term adjustments in the economy, disruption in the labor market or short-term cost-cutting at the expense of productive investment.

Table 4. Regression results of GMM.

GDP_GROWTH	Coef.	St. Err.	t-value	p-value	[95% Conf	Interval]	Sig
L	.012	.021	0.58	0.560	-.029	.054	
AI_ADOPT	2.351	.145	16.26	0.000	2.068	2.635	***
FIN_INCL	.049	.002	26.93	0.000	.046	.053	***
EFFICIENCY	-.029	.002	-12.87	0.000	-.033	-.025	***
GOV_QUAL	1.521	.038	40.42	0.000	1.447	1.594	***
SYS_RISK	-3.048	.193	-15.75	0.000	-3.427	-2.668	***
EDU	.21	.01	20.50	0.000	.19	.23	***

Mean dependent var	7.977	SD dependent var	2.093
Number of obs.	445		
Sargan/Hansan	0.1360	Chi-square	5059.135
AR (1)	0.0000		
AR (2)	0.4376		

*** p<.01, ** p<.05, * p<.1

Additionally, the findings show that governance quality (GOV_QUAL) and education level (EDU) positively affect GDP growth (GDP_GROWTH). The quality of governance is an underlying factor in laying the foundation of a stable and conducive environment of economic activities. Good governance, defined by effective policy implementation, low corruption, and efficient public administration, increases investor confidence, improves resource allocation, and stimulates sustainable development [16]. High-Institutional-quality countries have better macroeconomic stability, more foreign direct investment, and more efficient public service delivery [38] which are elements leading to economic growth. In addition, good governance strengthens legal and regulatory regimes that underpin entrepreneurship and innovation, which in turn enhances GDP growth [28].

Another major contributor to long-term economic growth is Education (EDU), which serves to improve human capital through increased labor productivity, innovation, and adaptability to technology. There is also substantial empirical evidence that higher education levels are positively related to economic output, since a better educated labor will be capable of pursuing more skill- and knowledge-intensive jobs [39]. Moreover, education raises creativity and the use of technology that helps in being competitive in a rapidly changing global economy [40]. One also knows that investment in education leads to social mobility and income equality, which in turn aids economic stability and growth [41]. The role of government quality and education in enhancing GDP growth underscores the significance of institutional reforms and human capital development for ensuring sustainable economic progress. That said, evidence indicates that governments focused on governance, effective implementation of public services, and on investing in education tend to achieve higher and more sustainable rates of economic growth.

On the contrary, systemic risk (SYS_RISK) reduces GDP. This result corroborates the existing literature, which indicates that the high systemic risk that results from financial instability, market volatility and macroeconomic imbalances, could impose an economic growth bar on the service sector through myth of uncertainty, declining investment and abated financial intermediation. Systemic risk is defined as the threat of disruption of the financial system in a way that could cause major decline of the economy [17]. When systemic risk is high, financial institutions become more likely to default, limiting the possibility of credit, thus making businesses less willing to invest or consumers to spend on extensive level [42]. This reduces economic activity and slows GDP growth. Additionally, financial crises induced by systemic risk can lead to capital flight, currency depreciation and fiscal imbalances, which exacerbate economic instability [43].

Empirical studies also demonstrate that increasing systemic risk prevents firm productivity and innovation because firms become more risk-averse and cut their in-vestments in research, technology, and expansion [44]. Moreover, governments might find themselves compelled to adopt contractionary fiscal and monetary measures in response to systemic risks [45], with tools like rising interest rates or reduced public expenditure adding to the economic malaise. As shown in this Paper, systemic risk severely compresses GDP growth, underscoring the need for financial stability, sound regulation, and crisis management policies to allow economies to operate at their potential. The priority for policymakers should be strengthening financial architecture, implementing strict mechanisms for risk management, and introducing targeted macroprudential policies to minimize systemic risks and promote better macroeconomic stability.

Table 5. Robustness results.

GDP_GROWTH	Coef.	St. Err.	t-value	p-value	[95% Conf	Interval]	Sig
L	.015	.019	-0.76	0.448	-.053	.023	
AI_ADOPT	2.127	.128	16.65	0.000	1.876	2.377	***
FIN_INCL	.048	.002	28.72	0.000	.044	.051	***
EFFICIENCY	-.031	.002	-15.02	0.000	-.035	-.027	***
GOV_QUAL	1.503	.036	42.21	0.000	1.434	1.573	***
SYS_RISK	-3.121	.181	-17.20	0.000	-3.476	-2.765	***
EDU	.198	.009	21.56	0.000	.18	.216	***
INF_RATE	-.004	.01	-0.34	0.737	-.024	.017	
INT_RATE	-.006	.012	-0.55	0.582	-.029	.016	
RD_EXP	-.019	.029	-0.67	0.503	-.075	.037	
Constant	3.922	.274	14.30	0.000	3.384	4.459	***
Mean dependent var		7.977		SD dependent var		2.093	

Number of obs.	356	Chi-square	6834.706
Sargan/Hansan	0.7707		
AR (1)	0.0000		
AR (2)	0.3517		

*** p<.01, ** p<.05, * p<.1

Table 5 presents the results of the robustness check using the difference GMM analysis, confirming the consistency of the findings with the system GMM results. The analysis reaffirms that AI adoption (AI_ADOPT), financial inclusion (FIN_INCL), governance quality (GOV_QUAL), and education level (EDU) positively impact GDP growth (GDP_GROWTH). Conversely, operational efficiency (EFFICIENCY) and systemic risk (SYS_RISK) exhibit a negative impact on GDP growth, reinforcing the robustness of the initial findings. These results suggest that the relationships identified in the system GMM estimation remain stable and reliable under an alternative GMM specification.

However, the robustness check results indicate that inflation rate (INF_RATE), interest rate (INT_RATE), and research & development expenditure (RD_EXP) negatively impact GDP. While inflation and interest rates are traditionally associated with negative economic effects, the negative impact of R&D expenditure may reflect short-term economic adjustments or inefficiencies in innovative investment. Higher inflation tends to distort economic decision-making, reduce purchasing power, and increase uncertainty, all of which can hinder GDP growth [74]. Inflation erodes consumer real income, leading to lower consumption and aggregate demand, which slows down economic expansion [75]. Moreover, high inflation can discourage long-term investments as firms face higher costs of production and price instability, reducing overall productivity and output [76]. The Phillips Curve theory suggests a short-run trade-off between inflation and unemployment, but prolonged inflation often leads to economic instability, which negatively impacts GDP [77]. Moreover, with higher interest rates firms and households experience the effect of borrowing cost increase and discourage investment and consumption [50]. Higher interest rates mean higher capital costs for firms; thus, they invest less in infrastructure, technology, and productive capacity, slowing economic growth [78]. Also, they suppress consumer purchases of large items, such as homes and durable goods, which diminishes economic activity [79]. This is in accordance with monetary policy theories, which imply that contractionary policies, such as increasing interest rates to slow inflation, typically lead to reduced GDP growth [80].

While the traditional view is that R&D expenditure should enhance economic growth, that negative effect in this study may reflect the adjustment costs of moving towards R&D or even inefficiencies in the innovation process or R&D efforts not immediately translating into productivity gains. Empirical evidence indicates that the positive results of R&D investments are typically subject to a long-term process [81], whilst in the short-term, expenditures on R&D hinder the immediate economic output. In addition, slow commercialization of innovations, or inefficient allocation of R&D funds or weak intellectual property protection in some economies [82] can constrain the expected returns on research investment. The Solow Growth Model reaffirms the importance of technological advancements for long-run growth but also emphasizes that it may take time for such advancements to be diffused and adapted which can cause a short-run slowdown in economic growth. Indeed, as investment and consumption are being depleted further in consequence of inflation and high interest rates, the R&D drag effect indicates that innovation policies must be accompanied at least by appropriate commercialization measures. That means preserving stable inflation, keeping interest rates and directed R&D investment at sensible levels that do not stifle growth.

VII. CONCLUSION

The study used the system Generalized Method of Moments (GMM) estimation technique to assess the effect of AI adoption, financial inclusion, and operational efficiency on GDP growth in 89 countries over the period 2018–2023. The findings affirm the importance of AI adoption and financial inclusion for economic growth, and how both digital and financial inclusivity can foster economic performance. Moreover, GDP growth is more systematically ordered by governance quality and education, thereby illuminating the importance of institutional robustness and human capital development across any path to sustainable economic advancement. But the study makes this finding, that GDP growth is negatively correlated with efficiency a surprising finding that contradicts classical expectations. Finally, systemic risk has a dampening effect on GDP, revealing the disruptive effects of financial vulnerabilities on macroeconomic stability. Additionally, difference GMM was used to make the results more robust, with INF_RATE, INT_RATE and RD_EXP included as extra economic, financial, and innovation variables. These findings confirm the robustness of the baseline analysis, confirming that AI adoption, financial inclusion, the quality of governance and education positively impact GDP growth, while efficiency and systemic risk negatively impact GDP growth. Likewise, the robustness check results confirm the negative effect of inflation, interest rates, and R&D expenditure on GDP growth, which implies that instability in the economy, high cost of borrowing money, and ineffective investment in innovation can negatively affect GDP growth. The findings have important implications for policymakers, including the need for better management of AI-based development, increased financial inclusion, alignment of the structure for governance and sharpening of macroeconomic policies for maintaining economic growth over the long-term.

VIII. POLICY IMPLICATIONS

These findings imply that: 1) governments and policymakers should enable and incentivise AI-led development, and 2) we need better financial inclusion and stronger governance systems to provide a foundation for continued growth. With AI adoption accounting for a substantial portion of GDP growth, it becomes imperative for policymakers to focus on initiatives that foster the responsible use of AI, such as investments in digital infrastructure and support for AI research and development, while also establishing regulatory frameworks that enable AI to flourish. And having learned how to capitalize on the economic opportunities presented by AI, equitable access to those AI-related skills through education and enhanced workforce training programs. Fintech innovation, digital banking, and regulatory backing are expanding financial inclusion, giving underserved people and businesses greater access to credit and investment prospects, promoting economic activity.

The inverse association between efficiency and growth complicates conventional economic solutions that are used to optimize efficiency. Ensure productivity gains are not a cost of employment and wages and aggregate demand. Systemic financial risk also has a negative external impact on GDP, making the case for the importance of strong financial system regulatory frameworks to ensure that regaining economic stability in a country is not just a mirage. Building these elements so that financial oversight is strengthened, risk management strategies improved and transparency in financial markets enhanced can help mitigate systemic risks in place, contributing to macroeconomic stability. In addition, the study points out that inflation, interest rates, and inefficient R&D spending can impede economic growth, stressing the need for balanced macroeconomic policies. By ensuring reasonable inflation and interest rates, governments will provide a stable environment for investment and consumption. Monetary policies need to be calibrated in pursuit of economic growth without hampering stability. Policymakers have to ensure that research and development expenditures are translated into productive eco-nomic gains by fostering stronger networks between research institutions and industry, promoting commercialization of innovations, and improving the allocation of public money to research.

In low- and middle-income countries (LMICs), the priority should be to build foundational digital ecosystems, promote inclusive fintech services, and close infrastructure and literacy gaps. AI-based financial services can accelerate economic participation in these regions if supported by investment in mobile connectivity, e-payment platforms, and basic digital skills training. Furthermore, regulatory sandboxes and simplified compliance regimes can facilitate innovation while protecting consumers. In contrast, high-income economies should lead in AI innovation by scaling R&D funding and building ethical AI governance systems that address algorithmic bias, data privacy, and systemic risk in financial markets. These nations must also address the efficiency-growth paradox where operational efficiency driven by AI and automation may suppress job creation, real wages, and aggregate demand. Thus, active labor market policies, such as universal upskilling and flexible social safety nets, are essential to ensure that AI-induced productivity gains are inclusive and sustainable. Across all regions and sectors, the inverse association between operational efficiency and GDP growth challenges conventional economic prescriptions. While automation enhances efficiency, it can inadvertently reduce employment and consumer spending. Policymakers must therefore balance productivity with employment, particularly in labor-intensive sectors like manufacturing and retail, by promoting AI-human collaboration models instead of full automation.

IX. LIMITATIONS AND FUTURE RECOMMENDATIONS

There are some limitations of this study that need to be addressed, despite the important information. First, the system GMM estimator (used in the current study) solves endogeneity issues, but it is sensitive to instrument selection and model specification potentially influencing the robustness of the results. Future research may consider alternative econometric methods, including panel cointegration methods or machine learning techniques, to corroborate these results. Second, this study concentrates on 89 countries which, although extensive in scope, might not fully account for regional heterogeneities and the distinctive economic dynamics found in smaller or less-developed economies. On this basis, the dataset could be extended periodically through the inclusion of more countries or through geographical specific analysis which could give better evidence of what AI adoption, financial inclusion, and operational efficiency impact GDP growth. Furthermore, the study does not explicitly differentiate between different levels of AI adoption or financial inclusion at the sectoral level, which may lead to overgeneralization. Future studies are also capable of working toward a sectoral modelling of productivity and growth effects of differential AI adoption between manufacturing, services, or even finance industries. Realizing how financial inclusion impacts different income groups or business range can lead to more customized proposals for policymakers. Also, inverse correlation between the operational effectiveness and the percentage growth basis of the GDP is a paradoxical finding further contradict/contrasting with conventional economics. Understanding more about the mechanisms fueling this relationship, like rigidity in the labour market, job displacement from automation, or structural inefficiencies, could help hone economic policy prescriptions.

Finally, it suggests that recent work-practice innovation may ultimately be undone by the R&D-overhead overhang effect, and the study is even less micro in its analysis when it identifies inflation, interest rates, and R&D expenditure as negative effects on GDP growth, without going deeper into the causal mechanism. Future studies could also revisit the role of inflationary expectations, and monetary policy paths, as well as the efficiency with which R&D is expended to support growth. Longitudinal case studies or intervention studies also could help identify how various policy measures affect these variables, with the goal of producing more actionable insights. It is also relevant to include qualitative data, such as expert opinions and firm-level case studies, which might provide more insights on the practical issues and impact of AI adoption, financial inclusion and governance reforms.

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Conflicts of Interest

The authors declare that they do not have any conflicts of interest.

Data Availability Statement

The data used in preparing this manuscript is available from the corresponding author upon reasonable request.

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