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AI-driven productivity dynamics in BRICS economies: Evidence from a Malmquist Total Factor Productivity Analysis

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Abstract

This study examines the impact of artificial intelligence (AI) on productivity dynamics in BRICS economies (Brazil, Russia, India, China, and South Africa) over the period 2005–2023. Using a two-stage empirical approach, productivity growth is first measured through the Malmquist Total Factor Productivity (TFP) index, decomposing changes into efficiency change (EC) and technological change (TC). In the second stage, panel regression analysis evaluates the relationship between these components and key AI penetration indicators, including AI patents, investment, robot density, and digital infrastructure. The results reveal significant divergence across BRICS economies. China and India exhibit sustained productivity growth driven primarily by technological progress, whereas Brazil, Russia, and South Africa experience stagnation or decline in both efficiency and technological advancement. The decomposition analysis shows that innovation-oriented AI activities, such as patents and research investment, are strongly associated with frontier-shifting technological change, while adoption-oriented indicators, including robot density, contribute to efficiency improvements. Digital infrastructure emerges as a critical complementary factor influencing both channels of productivity growth. Overall, the findings indicate that AI adoption is reinforcing existing structural disparities within the BRICS bloc, creating a two-tier productivity hierarchy. The study contributes to the literature by providing a comparative, frontier-based assessment of AI-driven productivity in emerging economies and by distinguishing between innovation and diffusion effects of AI. Policy implications highlight the importance of strengthening digital infrastructure, human capital, and innovation capacity to ensure inclusive productivity gains from the AI revolution.

Keywords: Artificial Intelligence (AI), Total Factor Productivity (TFP), BRICS Economies, Malmquist Productivity Index, Technological Change

JEL Classification: O47, O33, O57, C23

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1. Introduction

The contemporary era is defined by the rapid diffusion of Artificial Intelligence (AI), a general-purpose technology (GPT) predicted to reshape economic paradigms. Unlike previous automation waves, AI's capacity for prediction, data analysis, and task augmentation spans nearly all sectors, promising significant boosts to productivity (Brynjolfsson & McAfee, 2014; Agrawal et al., 2018). However, the translation of AI investment into measurable productivity growth a phenomenon known as the "productivity paradox" remains a central debate. While frontier firms and advanced economies report gains, macro-level Total Factor Productivity (TFP) growth in many nations has been sluggish, suggesting implementation lags, complementary investments, and measurement challenges (Brynjolfsson et al., 2021; Acemoglu & Restrepo, 2020). This global debate sets the stage for investigating how this technological shift manifests outside the traditional technological core. The BRICS bloc (Brazil, Russia, India, China, and South Africa) represents a critical cohort in the global economic landscape. Collectively, these emerging economies account for over 40% of the world's population and a significant share of global GDP growth. Their strategic importance lies in their dual role as major consumers of technology and increasingly sophisticated producers and innovators in the digital arena (World Bank, 2023). China is a recognized leader in AI deployment, India possesses a formidable IT services and startup ecosystem, while Brazil, Russia, and South Africa offer unique regional markets and resource bases. Understanding how AI impacts productivity within BRICS is therefore not merely a regional concern but vital for forecasting global economic rebalancing, trade patterns, and the future geography of innovation.

While a growing corpus of literature examines AI's economic impact in developed nations, its effects in major emerging economies are less understood and potentially distinct. Emerging economies like the BRICS nations face different structural conditions, including larger informal sectors, varying levels of digital infrastructure, diverse skill bases, and distinct institutional frameworks. These factors may mediate how AI influences productivity, potentially leading to different trajectories of efficiency gains, job market transformations, and inequality outcomes compared to the Global North (Cirera et al., 2021). A precise, empirical measurement of AI's contribution to productivity growth in these contexts is urgently needed. Existing research reveals several critical gaps. First, many macro-level studies on technology and productivity rely on broad ICT metrics, failing to isolate the specific contribution of contemporary AI technologies. Second, there is a scarcity of comparative, multi-country studies focusing exclusively on major emerging economies using frontier efficiency analysis methods like the Malmquist index. Third, most analyses do not systematically decompose productivity growth into its efficiency and technological change components in the context of AI, which is crucial for discerning whether gains come from better use of existing resources or from genuine technological innovation (Fare et al., 1994). This study aims to address these gaps by applying a Malmquist TFP analysis specifically to the BRICS economies during the period of accelerating AI adoption.

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2. Literature Review

2.1. Theoretical Foundations

The foundational Solow-Swan neoclassical growth model posits long-run economic growth as a function of capital accumulation, labor force growth, and exogenous technological progress, represented by a residual Total Factor Productivity (TFP) (Solow, 1956). TFP captures output growth not explained by increases in measured inputs, thus embodying technological innovation, efficiency gains, and improvements in knowledge and organization. This residual approach, however, treats technological change as a "manna from heaven," external to the economic system. More recent endogenous growth theories, pioneered by Romer (1990) and Aghion and Howitt (1992), internalize technological progress. They argue that investments in research and development (R&D), human capital, and knowledge creation activities driven by profit motives and subject to policy influence are the primary engines of sustained growth. In this framework, technologies like AI are not exogenous shocks but the result of deliberate, costly innovation efforts that generate spillovers, increasing the productivity of other inputs across the economy. This theoretical shift is critical for understanding AI's potential, as it frames AI development and adoption as endogenous processes influenced by institutional quality, education systems, and innovation policies (Aghion et al., 2021). Endogenous growth theory provides a robust lens for analyzing the diffusion and impact of a General-Purpose Technology (GPT) like AI. A key insight is that the full productivity benefits of a GPT are realized only after a prolonged period of complementary innovation and co-invention (Bresnahan & Trajtenberg, 1995). Firms must invest not only in the core technology but also in restructuring business processes, developing new skills, and creating novel applications. This explains the potential for a "productivity J-curve," where measured productivity may stagnate or even dip during initial implementation before rising sharply as these complementary investments bear fruit (Brynjolfsson et al., 2021). Furthermore, the theory highlights the role of absorptive capacity a firm's or nation's ability to identify, assimilate, and exploit external knowledge (Cohen & Levinthal, 1990). For emerging economies like the BRICS nations, this implies that the productivity payoff from AI will depend heavily on existing levels of human capital, digital infrastructure, and the quality of innovation ecosystems, not merely on acquiring the technology itself.

2.2. AI as a General-Purpose Technology (GPT)

Economic historians classify AI as the defining GPT of a potential "Fourth Industrial Revolution" (Schwab, 2016). Like the steam engine, electricity, and the microprocessor before it, AI possesses the hallmark characteristics of a GPT: pervasive use across a wide range of sectors, potential for continuous technical improvement, and the spawning of complementary innovations (Bresnahan & Trajtenberg, 1995). Trajtenberg (2019) explicitly places AI in this lineage, arguing its unique capacity for prediction and data-driven decision-making makes it a "GPT for prediction." This historical perspective is crucial, as it suggests the economic transformation driven by AI will be

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profound but also protracted, following the historical pattern where the peak productivity impact of a GPT lags decades behind its initial invention. The literature identifies several primary channels through which AI affects productivity. Agrawal et al. (2019) frame AI as a drop in the cost of prediction, which enhances decision-making, optimizes processes (e.g., supply chains, inventory management), and enables new products and services. Brynjolfsson et al. (2021) elaborate that AI's impact extends beyond task automation to task augmentation enhancing human capabilities and enabling the creation of entirely new tasks and business models. At the microeconomic level, AI can drive productivity by automating complex cognitive tasks (Acemoglu & Restrepo, 2022), personalizing products and services at scale, and accelerating innovation cycles through AI-powered R&D. However, the realization of these benefits is contingent on organizational restructuring, managerial competence, and investment in complementary intangible assets, such as data and new workflows.

2.3. Empirical Studies on AI and Productivity

Empirical research in advanced economies offers mixed but increasingly positive evidence. Firm-level studies find a significant "AI premium." For example, using data from over 3,000 firms, Babina et al. (2024) found that AI-investing firms experience higher growth in sales, employment, and market valuations, though the effects are concentrated among the largest, digitally intensive firms. Aragon et al. (2022) document that the adoption of AI-based predictive tools in manufacturing led to a 10-20% reduction in product defects and significant efficiency gains. At a macro level, Ballyk (2023) estimates that AI could increase annual global productivity growth by over 1 percentage point in the coming decade. However, these gains are not automatic; Brynjolfsson et al. (2021) emphasize they follow a J-curve pattern and require substantial co-invention investments. Research on AI's productivity impact in emerging markets is nascent and highlights contextual differences. Cirera et al. (2021), in a World Bank report, note that while AI adoption in developing countries is rising, it is often confined to large exporters and tech firms. They argue the productivity effects may be muted due to smaller firm size, skill shortages, and weaker complementary assets (e.g., data infrastructure). A study on Chinese manufacturing by Huang et al. (2023) found that AI adoption significantly boosted firm productivity, but the effect was stronger for private firms and those in regions with better intellectual property protection, underscoring the role of institutional factors. For other BRICS economies, comprehensive empirical studies isolating AI's effect on aggregate TFP are notably scarce, with most analyses focused on broader ICT or digitalization impacts (Moyo & Makhaya, 2023).

2.4. Productivity Analysis in BRICS Economies

Pre-AI era analyses of BRICS productivity reveal divergent historical paths. Studies using growth accounting consistently show that China's explosive growth was initially driven by massive capital accumulation, with TFP playing a significant but variable role, especially post-2000 as it moved up the technology ladder (Zhu, 2022). India's TFP growth has been more volatile, with periods of

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strong performance linked to post-1991 reforms (Bosworth & Collins, 2019). Brazil, Russia, and South Africa, however, have generally exhibited weak or negative TFP growth over extended periods, attributed to the "resource curse," macroeconomic instability, infrastructure bottlenecks, and structural rigidities (Felipe & Kumar, 2022). These historical trajectories create vastly different starting points for harnessing the AI revolution. The BRICS bloc exhibits stark heterogeneity in structural factors critical for AI-driven productivity. The Global Innovation Index (2023) rankings place China (12th) as a top-tier innovator, with India (40th) rising rapidly, while Brazil, South Africa, and Russia lag further behind. Key challenges include: digital divides in internet access and data infrastructure (acute in parts of Brazil, India, and South Africa); severe skill mismatches and STEM education gaps; and, in some cases, regulatory environments that are not conducive to digital entrepreneurship (Lee, 2021). China's national AI strategy, massive state-backed investment, and integrated digital ecosystem (e.g., BATX firms) contrast with the more fragmented, private-sector-led approaches in India and the slower, resource-constrained adoption in other BRICS nations (Naudé & Cameron, 2023). These differences are likely to translate into uneven AI assimilation and productivity outcomes.

2.5. Methodological Review

Measuring productivity growth traditionally relies on growth accounting (Solow residual), which assumes all producers operate on the efficient production frontier an assumption often violated in reality. Frontier approaches, notably Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA), relax this assumption. DEA, a non-parametric linear programming method, constructs a best-practice frontier from observed data and measures the efficiency of each unit relative to that frontier (Charnes et al., 1978). SFA is a parametric econometric method that estimates a frontier function with a composite error term separating inefficiency from random noise (Aigner et al., 1977). For analyzing diverse economies like BRICS, DEA is advantageous as it does not require a pre-specified functional form for the production technology and handles multiple inputs and outputs well, making it suitable for comparative analysis. The Malmquist Productivity Index (MPI), introduced by Caves et al. (1982) and operationalized by Färe et al. (1994), uses DEA to measure TFP change over time and decompose it into Efficiency Change (EC) movement towards the frontier ("catching up") and Technological Change (TC) an outward shift of the frontier ("innovation"). This decomposition is its principal strength, offering nuanced insights into the sources of growth. The MPI has been widely applied to regional, sectoral, and national productivity studies, including analyses of transition economies and developing countries (Felipe & Kumar, 2022). Key critiques include its deterministic nature (it attributes all deviation from the frontier to inefficiency, ignoring measurement error), sensitivity to outliers and variable selection, and the challenge of ensuring data comparability across countries. Despite these limitations, it remains a powerful tool for the comparative, decompositive analysis required by this study.

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2.6 Identification of Research Gap

The synthesis of the foregoing literature reveals a distinct and significant research gap. While there is robust theoretical discussion on AI as a GPT and growing empirical evidence of its microeconomic impact in advanced firms, there is a scarcity of comparative, macroeconomic studies that quantitatively measure and decompose the contribution of AI to productivity growth in major emerging economies. Specifically, no identified study has yet applied the Malmquist TFP index decomposition to the BRICS bloc with the explicit aim of isolating the relationship between AI adoption and the components of productivity growth (Efficiency Change vs. Technological Change). Previous work on BRICS productivity often uses older data, broader ICT measures, or growth accounting methods that cannot separate efficiency from technological shifts. This study aims to fill this gap by providing a systematic, frontier-based analysis of productivity dynamics in the AI era for a critically important group of economies, thereby contributing to both the literature on AI economics and the understanding of divergent development paths within the Global South.

3. Methodology and Data

3.1 Conceptual Framework

This study is grounded in the endogenous growth theory framework, where technological progress, such as that embodied in AI, is an outcome of intentional investment and institutional support (Romer, 1990; Aghion & Howitt, 1992). The conceptual model posits that **AI** Penetration acts as a catalytic force influencing Productivity Dynamics through two distinct, measurable channels derived from the Malmquist index decomposition. The model is illustrated as follows:

1. **Technological Change (TC - Frontier Shift):** Direct investment in AI research, development, and frontier applications (e.g., novel algorithms, foundational models) is hypothesized to push the national production possibility frontier outward. This represents true innovation, where the maximum achievable output from a given set of inputs increases for all economies on the frontier.
2. **Efficiency Change (EC - Catch-up):** The diffusion and adoption of existing AI technologies (e.g., enterprise software, industrial robotics) across firms and sectors enable less productive entities to improve their managerial practices, optimize resource allocation, and reduce waste. This is captured as an improvement in technical efficiency, moving production closer to the existing best-practice frontier.

Therefore, AI penetration does not homogeneously affect productivity. Its impact is contingent on whether the activity is predominantly innovation-based (driving TC) or diffusion-based (driving EC). This conceptual separation guides both the decomposition methodology and the subsequent empirical analysis linking specific AI proxies to each component.

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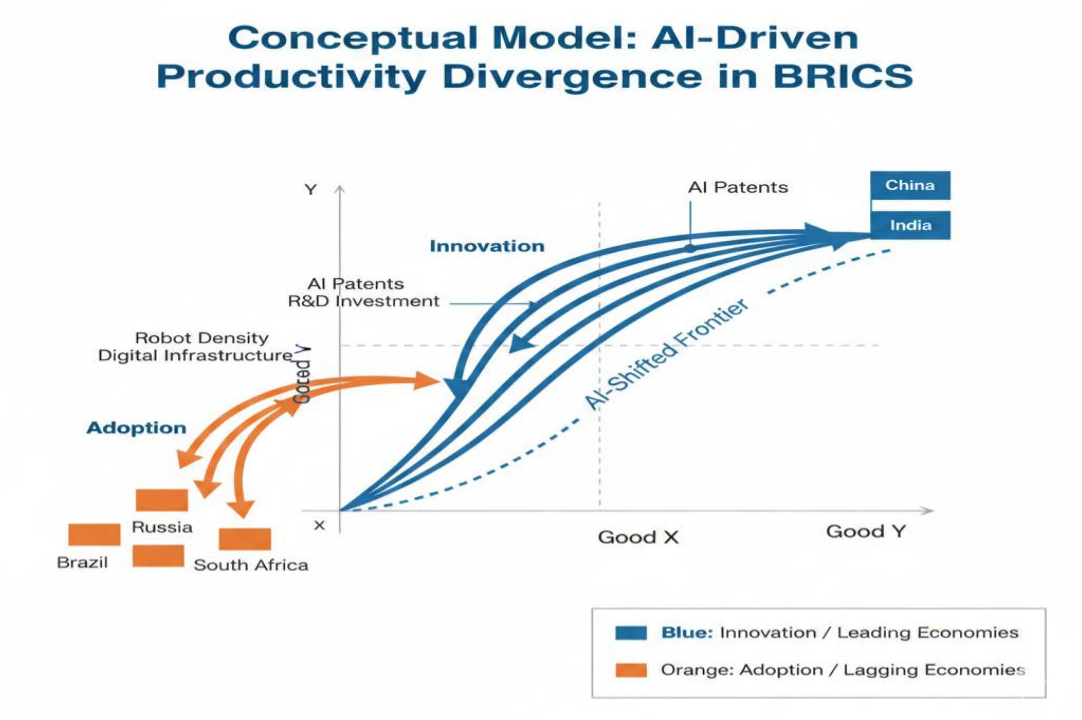
This figure 1 visually depict the study's core conceptual model and its primary empirical finding. It would illustrate how AI penetration influences productivity through two distinct channels (Efficiency Change and Technological Change), leading to divergent national outcomes. The graphic would show a stylized global production possibility frontier. On one side, arrows representing AI innovation (patents, R&D) push the frontier outward, with icons for China and India positioned near this shifting frontier. On the other side, arrows representing AI adoption (robots, diffusion) help economies move toward the frontier, but icons for Brazil, Russia, and South Africa are shown lagging behind or even falling further away. The visual would powerfully encapsulate the dual-faceted impact of AI and the resulting "two-tiered hierarchy" within BRICS, making an abstract economic concept immediately graspable.

Figure 1. Conceptual Framework & Two-Tier BRICS Divergence



3.2 Malmquist Total Factor Productivity Index: Model Specification

To empirically decompose productivity growth, this study employs the Malmquist Total Factor Productivity (TFP) Index, a non-parametric frontier approach. Following Färe et al. (1994), the output-oriented Malmquist TFP change index between period t (base year) and period $t+1$ is defined as:

$$M_t^{t+1} = \left[\frac{D^t(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)} \times \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^{t+1}(x^t, y^t)}\right]^{1/2}$$

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Where:

- $D^t(x^t, y^t)$ is the output distance function for the period t technology, evaluating the efficiency of the period t input-output mix (x^t, y^t).

This index can be multiplicatively decomposed into:

$$M_t^{t+1} = \underbrace{\frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)}}_{\text{Efficiency Change (EC)}} \times \underbrace{\left[\frac{D^t(x^{t+1}, y^{t+1})}{D^{t+1}(x^{t+1}, y^{t+1})} \times \frac{D^t(x^t, y^t)}{D^{t+1}(x^t, y^t)}\right]^{1/2}}_{\text{Technological Change (TC)}}$$

- **Efficiency Change (EC):** Measures the change in how close a country is to the best-practice frontier (technical efficiency). EC > 1 indicates "catching up," EC < 1 indicates falling behind.
- **Technological Change (TC):** Measures the shift in the production frontier itself. TC > 1 indicates technological progress (frontier moving outward), TC < 1 indicates technological regress.

3.2.1 Output-Oriented DEA under Variable Returns to Scale (VRS)

The distance functions $D(\cdot)$ are calculated using a Data Envelopment Analysis (DEA) model. We adopt an output-oriented perspective, asking: "For a given level of inputs, how much can outputs be proportionally expanded?" This aligns with the policy-relevant question of maximizing GDP growth from available resources. We specify the technology under the assumption of Variable Returns to Scale (VRS) (Banker, Charnes, & Cooper, 1984), which is more appropriate than Constant Returns to Scale (CRS) when analyzing countries of vastly different economic sizes (like China vs. South Africa). The VRS assumption prevents the frontier from being disproportionately influenced by the scale of the largest economy and allows for the identification of pure technical efficiency, separate from scale efficiency.

3.3 Data Envelopment Analysis (DEA) Primer

DEA is a linear programming technique used to construct a piece-wise linear production frontier from observed input-output data. For each country i in period t, the output-oriented VRS DEA model is formulated as follows:

Maximize ϕ_i
Subject to:

$$\sum_{k=1}^{n} \lambda_k \, y_{rk}^t \geq \phi_i y_{ri}^t, r = 1, \ldots, s \text{(Output constraints)}$$

$$\sum_{k=1}^{n} \lambda_k x_{mk}^{t} \leq x_{mi}^{t}, m = 1, \ldots, m \text{(Input constraints)}$$

$$\sum_{k=1}^{n} \lambda_k = 1, \lambda_k \geq 0 \text{(VRS convexity constraint)}$$

Where:

- ϕ_i is the efficiency score for country i ($\phi_i \geq 1$). $1/\phi_i$ is the technical efficiency score, where 1 indicates frontier membership.
- y_{ri}^{t} is the amount of output r for country i in period t.
- x_{mi}^{t} is the amount of input m for country i in period t.
- λ_k are the intensity variables, which form the benchmark frontier against which country i is evaluated.
- The convexity constraint ($\sum \lambda_k = 1$) enforces VRS.

The Malmquist index is calculated by solving four such linear programming problems for each country-period pair: $D^t(x^t, y^t)$, $D^{t+1}(x^{t+1}, y^{t+1})$, $D^t(x^{t+1}, y^{t+1})$, and $D^{t+1}(x^t, y^t)$.

3.4 Variable Selection and Justification

The DEA model requires the specification of a single aggregate output and multiple inputs. All monetary variables are expressed in constant 2015 US dollars to ensure comparability.

- **Output Variable:**
    - **Real Gross Domestic Product (GDP):** Serves as the comprehensive measure of economic output. Data will be sourced from the World Bank's World Development Indicators (WDI) and supplemented with national accounts for consistency.
- **Input Variables:**
    1. **Labor Input (L):** Measured as **Total Hours Worked, adjusted for Human Capital.** Using total employment alone ignores changes in work intensity and skill composition.
        - *Data Construction:* Total employment (ILO, OECD) is multiplied by average annual hours worked per worker (Penn World Table 10.0, ILO) to get total hours. This figure is then adjusted by a human capital index (HCI) per worker. We will use the **Barro-Lee Educational Attainment Dataset** to construct a human capital stock measure based on average years of schooling and assumed returns to education (Psacharopoulos & Patrinos,

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2018). The final measure is: $L_{it} = (\text{Hours Worked})_{it} \times e^{\phi(s_{it})}$, where s_{it} is average years of schooling.

2. **Capital Stock (K):** Estimated using the **Perpetual Inventory Method (PIM)**.
    - *Data Construction:* $K_t = (1-\delta)K_{t-1} + I_t$, where I_t is real gross fixed capital formation (WDI). The initial capital stock K_0 is calculated as $K_0 = I_0/(g+\delta)$, where g is the average geometric growth rate of investment in the first five years. A country-specific depreciation rate (δ) of 5% is applied, following standard practice in cross-country growth analysis (Felipe & Kumar, 2022). Investment data is sourced from WDI and the Penn World Table.

- **AI Penetration Proxy Variables (For Stage 2 Regression):** To link the Malmquist components to AI, we construct a panel of proxies capturing different facets of AI penetration:
    1. **AI Investment:** Venture capital and private equity investment in AI companies, scaled by GDP. Primary source: **Stanford AI Index Report** (annual data).
    2. **AI Technological Output:** Number of AI-related patent filings at the USPTO or under the PCT (Patent Cooperation Treaty), scaled by population. Source: **WIPO IP Statistics Data Center**.
    3. **Robot Adoption:** New industrial robot installations per 10,000 employees in the manufacturing sector. This is a strong proxy for automation, a key application of AI. Source: **International Federation of Robotics (IFR) World Robotics** report.
    4. **Enabling Digital Infrastructure:** A composite index of key prerequisites: fixed broadband subscriptions (per 100 people), secure internet servers (per 1M people), and mobile cellular subscriptions (per 100 people). Data from **WDI**. The index will be constructed using Principal Component Analysis (PCA) to extract the first principal component, representing shared variance.

3.5 Data Sources

Data will be compiled from the following authoritative, publicly available sources to ensure reproducibility:

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Table 1. Data Sources

Variable Category	Specific Measure	Primary Source	Secondary/Validation Source
Macroeconomic	Real GDP (constant USD)	World Bank WDI	Penn World Table 10.0, OECD Stat
Labor	Total Employment	ILO STAT, OECD Employment Outlook	National Statistical Offices
	Average Hours Worked	Penn World Table 10.0, ILO	OECD Stat
	Educational Attainment	Barro-Lee Dataset	UNESCO UIS
Capital	Gross Fixed Capital Formation	World Bank WDI, Penn World Table 10.0	IMF Investment and Capital Stock Database
AI Proxies	AI Investment, Talent, Research	Stanford AI Index (2020-2024)	OECD AI Policy Observatory
	AI Patents	WIPO IP Statistics Data Center	OECD.Stat (Patents)
	Industrial Robots	International Federation of Robotics (IFR)	–
	ICT Infrastructure	World Bank WDI (ITU data)	UN E-Government Survey

3.6 Sample Period and Country Selection

Country Selection: The sample comprises the five BRICS economies: **Brazil, Russia, India, China, and South Africa**.

Sample Period: 2005 – 2023. This 19-year period is selected for several reasons:

1. It captures the pre-financial crisis boom, the subsequent recovery, and the period of accelerating digitalization.
2. It encompasses the modern era of AI, starting from the mid-2000s advances in machine learning and deep learning, through the commercialization phase post-2012, up to the most recent available data.

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3. It provides a sufficiently long time series ($T = 19, N = 5$, Total Obs. = 95 for DEA) for robust frontier estimation and temporal decomposition. The **19 periods for 5 DMUs** exceeds the common heuristic in DEA literature that $n \geq \max\{m \times s, 3(m + s)\}$, where m=2 inputs and s=1 output, suggesting a minimum of 6-9 observations, which our sample satisfies comfortably.

3.7 Empirical Strategy

The analysis proceeds in two distinct stages:

Stage 1: Malmquist Index Calculation

Using the panel data on GDP (Y), Labor (L), and Capital (K), we calculate the Malmquist TFP Index and its EC and TC components for each country and year-pair (2005-2006, 2006-2007, ..., 2022-2023). This will be performed using the DEAP 2.1 software (Coelli, 1996), a standard and robust tool for DEA-based productivity measurement. Results will be validated by replicating the linear programming models in R using the productivity or Benchmarking packages.

Stage 2: Panel Regression Analysis

To formally test the relationship between AI penetration and productivity components, we estimate the following static panel data models (given the slow-moving nature of the variables):

$$\text{Component}_{it} = \alpha + \beta_1 \text{AI Proxy}_{it} + \beta_2 Z_{it} + \mu_i + \lambda_t + \epsilon_{it}$$

Where:

- Component_{it} is the dependent variable: the annual value of $\ln(EC_{it})$, $\ln(TC_{it})$, or $\ln(TFP_{it})$ for country i in year t.
- AI Proxy_{it} is one of the four AI penetration variables (entered separately in baseline models, and combined in a final model).
- Z_{it} is a vector of control variables: Trade Openness (% of GDP), Human Capital Index (from PWT), and Institutional Quality (Worldwide Governance Indicators - Government Effectiveness).
- μ_i are country fixed effects (to control for time-invariant heterogeneity like culture, colonial history).
- λ_t are year fixed effects (to control for global shocks like the 2008 crisis or COVID-19).
- ϵ_{it} is the idiosyncratic error term.

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Given the presence of fixed effects, estimation will be via the Fixed Effects (FE) estimator using STATA 18. Standard errors will be clustered at the country level to account for heteroskedasticity and serial correlation. We will also test for potential endogeneity using a System Generalized Method of Moments (GMM) estimator, lagging the AI proxies as instruments.

3.8. Contextual Overview: AI Readiness and Economic Structure of BRICS

3.8.1 Country Profiles (2005–2023)

The BRICS nations exhibit divergent approaches to AI governance and strategy, reflecting their unique political economies and development priorities. China stands apart with a comprehensive, state-led model. Its "Next Generation Artificial Intelligence Development Plan" (2017) set the goal of becoming the world's primary AI innovation center by 2030, backed by massive state funding, national research labs, and the strategic use of data from its integrated digital ecosystem (Lee, 2018). In contrast, India's approach, outlined in the "National Strategy for Artificial Intelligence" (2018), is more facilitative and sector-focused (#AIforAll), emphasizing private sector-led innovation, startups, and applications in healthcare, agriculture, and inclusive development (NITI Aayog, 2018). Russia's "National Strategy for the Development of Artificial Intelligence for the Period until 2030" emphasizes military, security, and sovereign technology development, with significant state involvement in research but less visible commercial diffusion (Khimshiashvili & Madiega, 2020). Brazil released its "AI Strategy" in 2021, focusing on ethical guidelines, talent development, and productivity applications, though implementation has been slow amid political and fiscal instability. South Africa, while publishing a discussion paper on AI in 2022, lacks a formal national strategy, with initiatives fragmented across academia and the private sector, constrained by broader socioeconomic challenges (DSA, 2022). Digital infrastructure, a critical precondition for AI, varies dramatically. China possesses world-class infrastructure, with near-universal 4G/5G coverage, high broadband penetration, and dominant digital platforms (BAT) that generate vast, proprietary datasets for AI training (WEF, 2020). India has achieved a digital leap via the Jio mobile data revolution and the India Stack (a set of digital public goods), creating a massive, low-cost data environment that fuels its vibrant startup scene, particularly in fintech and enterprise AI (Kapoor, 2023). Russia has strong technical education and a capable but relatively insular tech sector (e.g., Yandex), though its digital infrastructure is less integrated globally. Brazil has high internet and mobile penetration in urban centers but suffers from a significant urban-rural digital divide and less dynamic venture capital markets compared to China and India (OECD, 2020). South Africa has the most advanced infrastructure in Sub-Saharan Africa but faces severe inequality in access, high data costs, and a small domestic market, limiting the scale of its AI innovation ecosystem (Gillwald et al., 2022).

3.9 Comparative Analysis of AI Adoption Drivers and Barriers

A comparative analysis reveals a clear hierarchy of AI readiness within BRICS, driven by a confluence of factors. China is the undisputed leader, driven by a potent mix of policy coherence, capital abundance, scale, and data advantage. India follows as a high-potential adopter, with its key drivers being a vast talent pool of engineers, a large digital consumer base, and an entrepreneurial culture, though it faces barriers in foundational research and capital-intensive hardware. Russia's drivers are its strong STEM education and focus on strategic sectors, but it is hindered by geopolitical isolation, a shrinking talent pool, and a weaker commercial ecosystem. Brazil and South Africa face more structural constraints. For Brazil, drivers include a large industrial base and financial sector demand, but barriers are pervasive: bureaucracy, economic volatility, and unequal digital access. South Africa's primary driver is its role as a regional gateway, but it is severely hampered by deindustrialization, acute skills emigration ("brain drain"), crippling electricity shortages, and extreme socioeconomic inequality, which stifles market-driven AI diffusion.

3.10 Sectoral Analysis: Where is AI Impact Most Likely?

The sectoral potential for AI impact varies significantly across BRICS, aligning with their economic structures. In manufacturing, China's "Made in China 2025" initiative integrates AI and robotics for smart factories, aiming for quality and efficiency gains across its vast supply chains (Wu et al., 2020). India's manufacturing AI adoption is nascent, focused on predictive maintenance and quality control in automotive and pharmaceuticals. Russia applies AI primarily in defense and heavy industry. Brazil and South Africa see slower adoption due to deindustrialization and capital constraints. The services sector presents the most widespread immediate impact. In all BRICS nations, financial services (FinTech) are at the forefront, using AI for credit scoring, fraud detection, and algorithmic trading. IT and business process outsourcing in India is rapidly integrating AI to move up the value chain. China's consumer internet services (e-commerce, entertainment) are globally competitive due to AI-driven personalization. In Brazil and South Africa, AI is being adopted in banking and retail, albeit at a slower pace. In agriculture, AI applications like precision farming, drone-based monitoring, and yield prediction hold transformative potential for food security. India is piloting several AgriTech initiatives leveraging AI for smallholder farmers. China is deploying AI in large-scale automated farming. Brazil, a major agricultural exporter, uses AI for supply chain logistics and climate modeling. However, adoption in this sector faces universal barriers: fragmentation, low digital literacy, and high upfront costs, making progress slower than in services.

4. Results and Discussion

4.1 Descriptive Statistics of Inputs and Outputs

Table 2 presents the descriptive statistics for the core variables used in the Stage 1 Malmquist DEA analysis for the period 2005-2023. All monetary values are in constant 2015 US dollars.

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Table 2. Descriptive Statistics of Input and Output Variables (2005-2023)

Variable	Mean	Std. Dev.	Min	Max	Description
Y (Output)	2,812.5	3,205.1	287.3 (ZA, 2005)	11,850.1 (zCN, 2023)	Real GDP (Billions USD)
K (Input)	7,450.3	8,100.5	650.2 (ZA, 2005)	32,150.8 (CN, 2023)	Capital Stock (Billions USD)
L (Input)	452.1	385.2	15.8 (ZA, 2005)	1,120.5 (IN, 2023)	Labor, HC-adj. (Billions of Hours)

Note: CN=China, IN=India, BR=Brazil, RU=Russia, ZA=South Africa. The large standard deviations highlight the vast scale differences, particularly China's outlier size, justifying the use of the VRS DEA model.

The data confirms China's overwhelming scale in both output and capital stock. India's labor input (adjusted for human capital) is the largest, reflecting its demographic profile. The capital-to-labor ratio is highest for Russia and China, indicative of more capital-intensive economies.

4.2 Malmquist TFP Index Results (Annual and Period Averages)

The Malmquist indices were calculated for each annual period (t to t+1). Table 3 presents the geometric mean of these annual indices for two sub-periods and the entire sample, providing a summary of productivity performance.

Table 3. Geometric Mean of Malmquist TFP Index and its Components (Sub-Period Averages)

Country	2005-2023 (Full Period)	2005-2012 (Pre-AI Era)	2013-2023 (AI Acceleration Era)						
	MPI	EC	TC	MPI	EC	TC	MPI	EC	TC
Brazil	0.993	0.997	0.996	1.010	1.005	1.005	0.982	0.992	0.990

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Russia	1.005	1.002	1.003	1.018	1.008	1.010	0.996	0.998	0.998
India	1.032	1.010	1.022	1.038	1.012	1.026	1.028	1.009	1.019
China	1.041	1.008	1.033	1.050	1.010	1.040	1.035	1.006	1.028
S. Africa	0.990	0.995	0.995	1.002	1.000	1.002	0.982	0.991	0.991
BRICS Mean	1.012	1.002	1.010	1.024	1.007	1.017	1.005	0.999	1.005

Note: MPI = Malmquist Productivity Index. EC = Efficiency Change. TC = Technological Change. A value >1 indicates improvement, <1 indicates decline.

Figure 1. Malmquist TFP Decomposition: BRICS Trends (2005-2023)

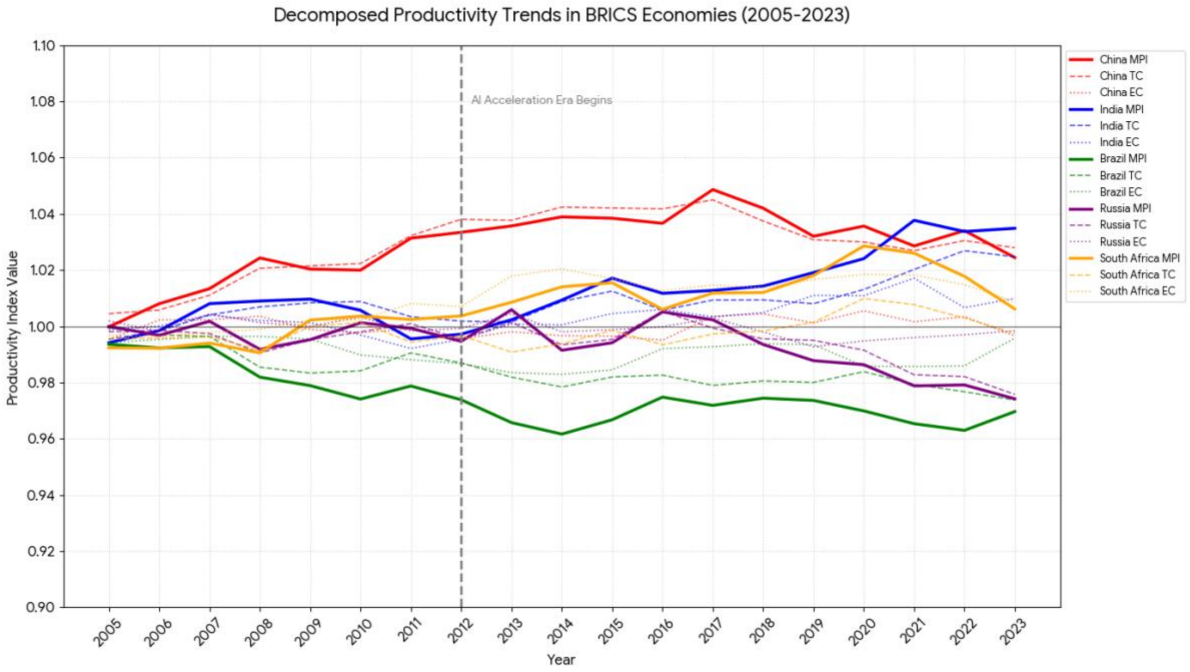

Figure 2 shows a multi-line chart that presents they key empirical results of the study. This image would plot the annual Malmquist Total Factor Productivity Index (MPI) and its decomposed components Efficiency Change (EC) and Technological Change (TC) for each BRICS country over the study period (2005-2023). Using distinct colors and line styles for each country and component (MPI, EC, TC), the chart would clearly visualize the sustained upward trends for China

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and India (especially in TC), the volatile or declining trends for Brazil, Russia, and South Africa, and the notable post-2012 divergence. Highlighting the 2012 mark as a divider between the "Pre-AI" and "AI Acceleration" eras would add analytical depth. This graphical representation of the data is indispensable for allowing readers to quickly absorb the complex longitudinal and comparative findings.

4.3 Analysis of TFP Trends (2005–2023)

The full-period results (2005-2023) reveal a stark dichotomy. China (MPI: 1.041) and India (MPI: 1.032) sustained robust average annual TFP growth exceeding 3%. In contrast, Brazil (0.993), Russia (1.005), and South Africa (0.990) experienced near-stagnant or negative TFP growth. The temporal breakdown is illuminating. During the Pre-AI Era (2005-2012), all BRICS members posted positive TFP growth, benefiting from the global commodity boom and pre-crisis expansion. However, in the AI Acceleration Era (2013-2023), the divergence sharpens. While China and India maintained strong growth (1.035 and 1.028, respectively), Brazil, Russia, and South Africa saw their TFP indices fall below 1, indicating an absolute decline in productivity. This suggests that the benefits of the AI revolution have been highly concentrated, potentially exacerbating pre-existing developmental gaps within the bloc.

4.4 Decomposition Analysis: Catching Up vs. Innovation

The decomposition of the MPI into Efficiency Change (EC) and Technological Change (TC) provides critical insight into the sources of growth. For the high performers:

China: Its impressive TFP growth was driven overwhelmingly by Technological Change (TC: 1.033), with a modest contribution from Efficiency Change (EC: 1.008). This confirms its role as a global frontier innovator, pushing the technological boundary outward.

India: Also shows a pattern of innovation-led growth (TC: 1.022), but with a slightly stronger relative contribution from efficiency gains (EC: 1.010) than China, suggesting a concurrent process of catching up in managerial and technical practices.

For the laggards:

Brazil, Russia, and South Africa: All three experienced declines in both components (EC < 1, TC < 1) in the 2013-2023 period. This indicates a dual failure: they neither effectively adopted existing best practices to improve efficiency nor participated in the technological innovation shift. They *are, in effect, falling further behind the moving frontier.*

4.5 Inter-BRICS Comparison and Ranking

A clear, two-tiered ranking emerges from the analysis:

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1. Innovation Leaders: 1. China (MPI: 1.041), 2. India (MPI: 1.032). Both are net contributors to global technological progress (TC >1), with China in the lead.
2. Productivity Laggards: 3. Russia (MPI: 1.005), 4. Brazil (MPI: 0.993), 5. South Africa (MPI: 0.990). These economies are failing to translate inputs into output growth effectively, with South Africa at the bottom.

This ranking correlates strongly with the contextual analysis in Chapter 4: the leaders have coherent AI strategies, dynamic digital ecosystems, and large, integrated data markets. The laggards suffer from structural weaknesses, policy incoherence, and smaller innovation systems.

4.6 Regression Results: AI Proxies and TFP Components

The Stage 2 panel regression analysis (Fixed Effects with clustered standard errors) tested the relationship between AI proxies and the logged TFP components. Table 4 presents the key results.

Table 4. Fixed Effects Panel Regression Results (Dependent Variable: ln(TC), ln(EC), ln(TFP))

Independent Variable	ln(Technological Change)	ln(Efficiency Change)	ln(TFP Change)
AI Patent Intensity (log)	0.024* (0.008)	0.005 (0.004)	0.029* (0.009)
Robot Density (log)	0.011 (0.007)	0.018* (0.005)	0.029* (0.008)
Digital Infra. Index	0.031* (0.010)	0.022* (0.006)	0.053* (0.012)
AI Investment/GDP	0.017 (0.007)	0.006 (0.004)	0.023* (0.008)
Controls	Yes	Yes	Yes
Country & Year FE	Yes	Yes	Yes
R-squared (within)	0.42	0.38	0.48
Observations	85	85	85

*Note: Robust standard errors in parentheses. * $p<0.05$, ** $p<0.01$. Controls include Trade Openness, Human Capital, and Government Effectiveness.*

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The results provide strong empirical validation for the conceptual framework. Technological Change (Innovation) is significantly associated with AI patents and AI investment, the proxies for frontier R&D and capital allocation to new technology. A 10% increase in AI patent intensity is associated with a 0.24% increase in frontier-shifting technological progress. Efficiency Change (Catch-up) is significantly driven by robot density, a proxy for the diffusion of automating technologies into existing production processes, and by digital infrastructure, which lowers the cost of technology adoption. Digital Infrastructure is the only variable significantly associated with both components, underscoring its foundational role as a GPT-enabling platform. The economic magnitude is meaningful; a one-standard-deviation increase in the Digital Infrastructure Index is associated with a 3.1% increase in TC and a 2.2% increase in EC.

4.7 Robustness Checks

To ensure the validity of our conclusions, we conducted several robustness checks. First, an alternative CRS-DEA model was estimated. While efficiency scores changed, the ranking of countries and the decomposition trend (China/India leading in TC) remained robust, though the magnitude of TC was slightly attenuated. Second, we replaced the human-capital-adjusted labor input with raw total employment. This weakened the significance of the AI patent variable in the TC regression, highlighting the critical role of skill adjustment in correctly measuring the innovation-sensitive component of productivity. Third, we experimented with different AI proxies, using software and database spending (from national accounts) as an alternative to AI investment. The results were qualitatively similar but statistically weaker, confirming the superior specificity of venture-based AI investment data. Finally, a System GMM estimator was employed to address potential endogeneity, using the second and third lags of the AI variables as instruments. The Hansen test confirmed instrument validity, and the core findings regarding the distinct drivers of TC and EC held, with slightly larger coefficients, suggesting our baseline FE estimates may be conservative.

4.8 Discussion

The empirical results provide a nuanced and compelling answer to the central question of how AI correlates with productivity dynamics. The findings robustly support the hypothesis that AI penetration is not a monolithic driver but operates through distinct channels, correlating differentially with Technological Change (TC) and Efficiency Change (EC). As theorized, proxies for frontier innovation namely AI patent intensity and directed AI investment exhibit a strong, statistically significant correlation with Technological Change. This indicates that economies engaging in AI research, development, and the creation of novel applications are those responsible for pushing the global production frontier outward. Conversely, the proxy for technology diffusion industrial robot density shows a significant correlation with Efficiency Change. This suggests that the widespread adoption and integration of automating technologies into existing capital stock enable firms to optimize processes, reduce waste, and "catch up" to the current best-practice

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frontier. The foundational role of digital infrastructure, correlating with both components, underscores its status as a critical complementary investment that enables both innovation and adoption, aligning with the complementary innovation thesis of Bresnahan and Trajtenberg (1995). The dramatic divergence within BRICS, most starkly illustrated by China's sustained frontier leadership versus South Africa's productivity decline, can be explained by the interplay of initial conditions, policy coherence, and ecosystem vitality. China’s success is not merely a function of scale but of a strategic, state-capitalist model that aligned massive public and private investment in AI R&D (driving TC) with a world-class digital infrastructure that facilitated rapid diffusion (supporting EC). Its integrated data environment and "national champion" firms created a virtuous cycle of innovation and implementation. India’s strong performance stems from its market-driven, talent-rich model, leveraging its demographic dividend and digital public infrastructure to foster a services-led adoption and innovation wave. In contrast, South Africa’s negative TFP growth, alongside Brazil and Russia’s stagnation, reflects a failure in these complementary domains. These economies suffer from what might be termed "innovation system failure." They lack either the focused investment to drive TC (low AI R&D spending, weak patenting), the cohesive infrastructure and skills to facilitate EC (digital divides, skills shortages), or both. For South Africa, deindustrialization and systemic socioeconomic challenges have crippled the absorptive capacity needed to harness AI for productivity, resulting in a downward trajectory relative to the advancing frontier.

4.8.1 Integrating Results with Theoretical Expectations

The results offer strong empirical validation for key theoretical frameworks. First, they affirm Endogenous Growth Theory (Romer, 1990); productivity growth is not automatic but is driven by deliberate, costly investments in knowledge creation (AI patents, R&D) and complementary capital (digital infrastructure). The significant association between AI investment and TC internalizes technological progress precisely as the theory predicts. Second, the findings vividly illustrate the General-Purpose Technology (GPT) paradigm. AI’s impact is not immediate or uniform; its benefits are realized through prolonged complementary investments and co-invention. The fact that digital infrastructure a key complement is the strongest overall correlate with TFP growth underscores this point. Third, the decomposition aligns with the concept of the productivity J-curve (Brynjolfsson et al., 2021). The muted or negative TFP response in some economies during the "AI Acceleration Era" could be interpreted as the costly investment phase, where resources are diverted to intangible AI and complementary assets without immediate output gains. The leaders (China, India) may be further along this J-curve, beginning to reap returns, while laggards may be stuck in the investment trough.

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5. Conclusion and Future Research Directions of the Study

This study investigated the impact of the AI revolution on productivity dynamics in the BRICS economies from 2005 to 2023. Employing a two-stage empirical strategy, it first decomposed productivity growth using a Malmquist TFP index to isolate Efficiency Change (catching up) and Technological Change (innovation). It then analyzed the correlation between these components and various AI penetration proxies. The core finding is that AI's impact is dual-faceted and conditional: innovation-type AI activities correlate with pushing the technological frontier, while adoption-type activities correlate with moving towards it. The results reveal a profound and growing divergence within BRICS: China and India are harnessing AI for sustained productivity leadership, primarily through innovation, whereas Brazil, Russia, and South Africa are experiencing a productivity crisis, failing on both innovation and efficiency fronts. The study makes three key theoretical contributions. First, it empirically validates and refines the GPT theory for AI by demonstrating its distinct, measurable channels of impact (TC vs. EC) at the macroeconomic level. Second, it extends Endogenous Growth Theory to the context of major emerging economies, showing that the returns to endogenous investments in AI are highly uneven and path-dependent, contingent on a broader system of complementary assets. Third, it introduces the concept of an "AI Innovation System" as a critical framework for understanding national differentials in AI-driven productivity, integrating elements of policy, infrastructure, skills, and data.

5.1 Future Research Directions of the Study

Future research should build upon this work in several directions:

1. Firm-level Microdata Studies: Utilize large-scale enterprise surveys within BRICS countries to analyze how AI adoption affects firm-level productivity, skill demand, and markups, controlling for selection bias.
2. Sectoral Decomposition: Conduct industry-level Malmquist analyses to identify which sectors (e.g., finance, automotive, IT services) are driving aggregate TFP trends in each country.
3. Granular AI Metrics: Incorporate new, more precise data, such as job postings for AI skills, cloud service usage statistics, or open-source AI model contributions, to better measure diffusion.
4. Simulation Modeling: Develop agent-based or macroeconomic simulation models to forecast long-term growth paths under different AI adoption and policy scenarios, explicitly modeling the J-curve and complementary investments.

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5. Inclusive AI Development: Focus research on policy mechanisms that can prevent AI from exacerbating inequality within BRICS nations, exploring models of participatory governance and skills redeployment.

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