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The Cognitive Toll of AI: Algorithmic Over-Reliance and Macroeconomic Volatility in Institutionally Heterogeneous Emerging Economies.

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The Cognitive Toll of AI: Algorithmic Over-Reliance and Macroeconomic Volatility in Institutionally Heterogeneous Emerging Economies.

Abstract

Artificial intelligence (AI) is transforming economies, but dominant narratives treat it merely as an automation tool or productivity shock, overlooking its deeper cognitive role. This study reconceptualizes AI as Algorithmic Cognitive Augmentation (ACA)—a technology that reshapes how economic agents process information and make decisions. By bridging behavioral macroeconomics with the economics of AI, we provide the first systematic analysis of AI's impact on macroeconomic stability through cognitive rather than purely productive channels.

We argue that the macroeconomic impact of ACA is nonlinear. Using a novel Cognitive Augmentation Index (CAI) for 20 institutionally heterogeneous emerging economies over 2005–2024, we employ Panel Smooth Transition Regression and Momentum Threshold Autoregression to identify a robust inverted U-shaped relationship. Moderate ACA is associated with higher total factor productivity, but beyond a critical threshold (CAI ≈ 0.41), over-reliance coincides with behavioral rigidities—automation bias, skill atrophy, and strategic homogenization—which are associated with a 15–25% higher macroeconomic volatility (95% CI: 12.4–27.8%).

Crucially, these patterns are strongly conditioned by institutional context: economies with weaker governance, digital infrastructure, and human capital adaptability face lower beneficial thresholds and steeper declines. Adjustment exhibits hysteresis, meaning recovery from over-reliance is slow and asymmetric.

Our findings are difficult to reconcile with the assumption that AI adoption is uniformly stabilizing. They highlight the need for context-sensitive AI governance that aligns algorithmic integration with institutional and cognitive readiness, especially in economies undergoing rapid but uneven digital transformation.

Keywords: Artificial Intelligence, Cognitive Augmentation, Nonlinear Dynamics, Threshold Effects, Emerging Economies, Behavioral Macroeconomics, Algorithmic Governance.

JEL : O33, E32, D83, O47, C23

Introduction

The rapid diffusion of artificial intelligence (AI) is transforming contemporary economies. Dominant economic narratives, however, continue to frame AI primarily as a productivity-enhancing or labor-displacing technological shock (Acemoglu & Restrepo, 2019; Brynjolfsson et al., 2021). While this literature has advanced our understanding of how AI reshapes production functions, it largely overlooks a deeper transformation: AI increasingly alters the cognitive architectures through which economic agents process information, form expectations, and make decisions. This paper argues that the macroeconomic effects of AI are mediated not only through automation but through algorithmic cognitive augmentation (ACA).

ACA is not modeled as a purely exogenous technological shock nor as a fully internalized individual choice. At the microeconomic level, agents optimally choose their degree of reliance on algorithmic systems based on relative signal precision and associated costs. At the macroeconomic level, ACA emerges as a systemic cognitive externality: individual reliance decisions generate aggregate effects—such as strategic homogenization, correlated errors, and erosion of cognitive diversity—that are not internalized by agents. Consequently, ACA is best understood as an emergent property of the decision environment, shaped by institutional constraints, digital infrastructure, and human capital rather than as a conventional factor input. This distinction is critical for explaining why excessive algorithmic integration may generate nonlinear and potentially destabilizing macroeconomic outcomes.

The analysis focuses on institutionally heterogeneous semi-emerging economies, characterized by intermediate institutional development, rapid yet uneven digital adoption, and structural dualism between formal and informal sectors. Development economics identifies these economies as occupying a fragile transition zone in which institutional capacity is still evolving while exposure to advanced technologies accelerates (Rodrik, 2007; Acemoglu & Robinson, 2012). Fragmented governance, incomplete regulatory frameworks, and uneven human capital formation create conditions under which algorithmic technologies may generate sharper nonlinear effects than in either advanced or low-income economies. Unlike advanced economies with consolidated institutions or low-income countries with limited algorithmic penetration, semi-emerging economies face the dual challenge of institutional upgrading and rapid cognitive integration of AI, making them particularly vulnerable to behavioral rigidities induced by over-reliance.

A growing interdisciplinary literature shows that algorithm-assisted decision systems can both mitigate and amplify cognitive biases, reshape attention allocation, and alter learning

dynamics (Gabaix, 2019; Kleinberg et al., 2018). Algorithms increasingly function as cognitive complements within firms, households, and public institutions (Agrawal et al., 2018; Rahwan et al., 2019). Yet, despite advances in behavioral macroeconomics incorporating bounded rationality and attention constraints (Angeletos & Lian, 2018; Gabaix, 2020), cognitive frictions are generally treated as exogenous. Existing frameworks rarely consider that AI systematically modifies these frictions.

Importantly, ACA is analytically distinct from conventional measures of digitalization or ICT diffusion. Standard indicators capture infrastructure and connectivity but not the extent to which algorithms are embedded in economically meaningful decision processes. Economies with similar ICT penetration may therefore differ substantially in how algorithms affect prediction, coordination, and judgment. This motivates our shift from infrastructure-based metrics toward a functional measure of algorithmic cognitive integration.

Emerging evidence suggests nonlinear relationships between technological adoption and economic performance. The ICT literature documents threshold effects and complementarities between technology, organization, and skills (Brynjolfsson & Hitt, 2000; Bloom et al., 2012). Theory further indicates that algorithm-driven expectations may either stabilize learning or, if excessively homogenized, amplify systemic volatility (Gabaix & Koijen, 2020; Farboodi et al., 2020). These insights remain weakly connected to the cognitive dimension of AI and are rarely tested in semi-emerging economies. Three gaps persist: (i) AI is largely studied as a productivity shock rather than a cognitive transformation; (ii) behavioral macroeconomics treats cognitive frictions as static; and (iii) empirical work relies mainly on linear models and developed-economy samples, overlooking threshold effects in heterogeneous institutional contexts. This paper addresses these gaps by conceptualizing ACA as a dual-edged mechanism: moderate algorithmic assistance reduces decision frictions, whereas excessive reliance induces automation bias, strategic homogenization, and skill atrophy (Bainbridge, 1983; Parasuraman & Manzey, 2010). The central prediction is an inverted U-shaped relationship between cognitive augmentation and macroeconomic performance.

To test this hypothesis, we construct a novel Cognitive Augmentation Index (CAI) for a balanced panel of 20 semi-emerging economies across five regions over 2005–2024. Endogeneity is addressed using instrumental variables (lagged neighbor CAI and submarine cable landings), and nonlinear dynamics are estimated through Panel Smooth Transition Regression and Momentum Threshold Autoregression models, allowing identification of regime-dependent effects and asymmetric adjustment.

The paper makes three contributions. First, it integrates algorithmic cognitive augmentation into a macroeconomic framework of productivity and volatility. Second, it provides cross-country evidence of a nonlinear threshold (CAI $\approx$ 0.41), beyond which algorithmic over-reliance is associated with 15–25% higher macroeconomic volatility and exhibits hysteresis. Third, it derives policy implications for managing human–algorithm interactions through context-sensitive governance, algorithmic diversification, and adaptive investment strategies.

By introducing algorithmic augmentation as a modifiable cognitive friction, this study contributes to behavioral macroeconomics; by shifting attention from automation to cognition, it advances the economics of AI; and by focusing on semi-emerging economies, it informs development debates on digital transition. Rather than asking whether AI raises productivity on average, the paper examines how algorithmic systems reshape macroeconomic stability by transforming cognitive decision architectures and why these effects are nonlinear and context-dependent. The remainder of the paper is organized as follows: Section 1 reviews the literature; Section 2 presents the framework and hypotheses; Section 3 describes data and methods; Section 4 reports results; Section 5 discusses heterogeneity and validation; and Section 6 concludes with policy implications.

1. Literature Review

1.1. Theoretical Foundations: From Production Functions to Cognitive Architectures

The dominant economic paradigm conceptualizes artificial intelligence (AI) as a general-purpose technology primarily affecting production processes and total factor productivity. Within this framework, AI is modeled as a technological shock that augments productivity while reshaping labor markets through automation and task reallocation (Acemoglu & Restrepo, 2018; Trajtenberg, 2018). Empirical evidence documents heterogeneous productivity effects, often characterized by delayed gains following substantial adjustment costs (Brynjolfsson et al., 2021). Recent contributions further emphasize accelerating diffusion and complementarities with institutional and organizational factors, particularly in developmentally heterogeneous contexts (Goldfarb et al., 2024; World Bank, 2024).

Despite these advances, production-centered models implicitly assume invariant decision-making architectures. By treating AI as an exogenous productivity shifter, they abstract from the possibility that algorithms reshape how agents form expectations, process information, and coordinate actions. Yet contemporary AI increasingly functions as a cognitive complement rather than a purely mechanical input (Agrawal et al., 2018). Ignoring this dimension limits the explanatory power of standard models, especially for macroeconomic stability and adjustment dynamics.

Behavioral macroeconomics partially addresses these limitations by incorporating bounded rationality and inattention. Gabaix (2020) shows how cognitive constraints shape macroeconomic responses, while diagnostic expectations provide microfoundations for cyclical dynamics (Bordalo et al., 2018). However, cognitive frictions are typically treated as structurally fixed, neglecting the possibility that technological systems endogenously modify their nature and persistence. This gap motivates an integrated framework linking AI's productivity effects to its role in reshaping cognitive architectures.

1.2. Cognitive Augmentation Mechanisms: Benefits, Risks, and Aggregation Challenges

A large interdisciplinary literature documents the micro-level benefits of algorithmic decision support. In medical diagnostics, finance, and labor markets, AI improves accuracy, consistency, and predictive performance by processing high-dimensional information more efficiently than human cognition alone (Rajkomar et al., 2019; Begenau et al., 2021; Cowgill & Tucker, 2020). These gains stem from advantages in pattern recognition, speed, and scalability.

At the same time, substantial evidence highlights cognitive risks. Automation bias may induce systematic errors when users overtrust algorithmic outputs (Parasuraman & Manzey, 2010). Widespread adoption of similar systems can generate herding behavior and correlated decision errors (Brynjolfsson & McAfee, 2017). Prolonged reliance may also lead to skill atrophy, weakening adaptive capacity (Bainbridge, 1983), while limited interpretability complicates oversight and accountability (Rahwan et al., 2019). Cognitive science further shows that algorithmic assistance can reduce effort but erode vigilance (Kahneman, 2011; Parasuraman & Manzey, 2010). Management research highlights an automation–augmentation paradox, whereby poorly calibrated integration undermines organizational learning (Raisch & Krakowski, 2021).

The central challenge lies in aggregation. Individual automation bias may translate into systemic rigidity, while algorithmic herding can amplify macroeconomic volatility. Existing models linking AI and expectations suggest either stabilization through improved learning or destabilization through synchronized forecasting errors (Gabaix & Koijen, 2020; Farboodi et al., 2020), but they focus narrowly on prediction tasks and abstract from broader cognitive transformations and heterogeneous adoption.

1.3. AI, Inequality, and Algorithmic Governance

A growing literature examines the distributional and governance implications of AI. Algorithmic technologies may exacerbate inequality by favoring capital-intensive production,

reinforcing digital divides, and embedding biases (Acemoglu, 2021; Lambrecht & Tucker, 2019; Cowgill & Tucker, 2020). This has motivated calls for governance frameworks emphasizing transparency, accountability, and fairness (Rahwan et al., 2019; World Bank, 2023).

Recent studies extend these concerns to emerging and semi-emerging economies, where regulatory capacity is often limited (UNCTAD, 2023; UNCTAD, 2024). Beyond income and access disparities, algorithmic diffusion may generate cognitive inequality, as uneven cognitive augmentation across sectors widens productivity gaps and increases systemic fragility. By identifying threshold effects and context-dependent risks, this study contributes to the governance debate by emphasizing adaptive, institution-sensitive regulation rather than uniform policy transfer.

1.4. Nonlinear Dynamics, Institutional Context, and Empirical Challenges

The ICT literature provides strong evidence of nonlinear adoption dynamics. Productivity gains often materialize only after complementary investments reach critical levels, generating threshold effects and path dependence (Brynjolfsson & Hitt, 2000; Katz & Shapiro, 1994). These insights motivate the use of threshold and smooth transition models to capture regime dependence (Hansen, 2000; González et al., 2017).

The economics of attention offers additional grounding. Rational inattention models show how information-processing constraints shape macroeconomic dynamics (Sims, 2003; Gabaix, 2019). By altering information costs and attention allocation, AI may fundamentally change how agents respond to shocks.

Institutional context is particularly salient in emerging and semi-emerging economies. While technological leapfrogging is possible, success depends on institutional quality, regulatory capacity, and human capital adaptability (Lee et al., 2020; Banerjee & Duflo, 2020). Weak data governance and limited oversight increase vulnerability to premature or excessive algorithmic reliance (World Bank, 2023). Nevertheless, most empirical studies rely on linear models and developed-economy samples, leaving nonlinear cognitive effects in institutionally heterogeneous contexts largely unexplored.

Table 1: Research Gaps and Theoretical Positioning

Dimension	Existing Literature	Limitations	Our Contribution
Theoretical Framework	AI as GPT; Behavioral macroeconomics	Disconnected approaches; Static cognitive assumptions	Integrated ACA framework; Dynamic, modifiable cognitive frictions

Cognitive Mechanisms	Micro-level human-AI interaction studies	No macroeconomic aggregation; Limited attention to nonlinearities	Models aggregate cognitive effects; Formalizes threshold dynamics
Empirical Approach	Linear adoption models; Developed economy focus	Neglects nonlinear effects; Lacks contextual specificity	PSTR/MTAR models; Focus on institutional heterogeneity in semi-emerging economies
Policy Implications	Generic governance frameworks	Neglects cognitive dimension; One-size-fits-all	Cognitive governance framework; Context-sensitive, readiness-based regulation

This study addresses these gaps by integrating cognitive augmentation into a nonlinear macroeconomic framework and empirically testing its implications in semi-emerging economies. By combining advanced econometric techniques with a theory-driven measure of algorithmic integration, it provides the first systematic assessment of how AI-induced cognitive transformations shape productivity and macroeconomic volatility across heterogeneous institutional contexts.

2. Theoretical Framework and Research Design.

Our framework focuses on semi-emerging economies, where rapid yet uneven digital adoption, institutional heterogeneity, and the coexistence of formal and informal sectors amplify both the benefits and risks of Algorithmic Cognitive Augmentation (ACA). In these contexts, algorithms often enter decision-making faster than institutions, human capital, and governance can adapt, making cognitive externalities especially important.

2.1. Conceptualizing Algorithmic Cognitive Augmentation

We define AI as Algorithmic Cognitive Augmentation (ACA): the systematic integration of algorithms into human decision-making across firms, labor markets, and public institutions. Unlike traditional technologies that directly boost productivity, ACA changes how agents gather information, form expectations, and make choices under uncertainty. Algorithms act as cognitive complements, lowering information-processing costs while reshaping attention, learning, and judgment.

Agents face standard informational and cognitive constraints, as in bounded rationality and rational inattention models (Simon, 1955; Sims, 2003; Gabaix, 2019). ACA relaxes these constraints by providing forecasts, recommendations, and automated evaluations, reducing the marginal cost of processing information. At low to moderate levels, this improves efficiency by lowering decision noise. But higher algorithmic reliance can induce correlated actions and beliefs across agents, increasing systemic risk.

We model ACA as a continuous variable affecting cognitive capacity, which is non-monotonic in algorithmic intensity. Initial augmentation enhances capacity, but overreliance can lead to rigidity, automation bias, reduced vigilance, and skill erosion (Bainbridge, 1983; Parasuraman & Manzey, 2010). This non-monotonicity motivates a nonlinear macroeconomic representation of ACA.

2.2. Micro-Founded Decision-Making under ACA

2.2.1. Information Structure and Cognitive Technology

Consider an agent i in country c at time t who chooses an action contingent on an unknown x_{ict} true state ω_{ict}. The agent acquires information through two channels:

1. Human Cognition: Generates a noisy signal $S_{ict}^{H} \sim \mathcal{N}(\omega_{ict}, \sigma_H^2)$ at a constant $costk_H > 0$. The precision of human judgment, $\frac{1}{\sigma_H^2}$, is increasing in the agent's endowed human capital, h_{i0}.
2. Algorithmic Assistance: Generates a signal $S_{ict}^{A} \sim \mathcal{N}(\omega_{ict}, \sigma_A^2)$ at cost k_A (ACA_{ct}), which decreases with the aggregate level of Algorithmic Cognitive Augmentation ACA_{ct}. Algorithmic precision $1/\sigma_A^2$ is increasing in the country's digital infrastructure quality, Dig_{ct}.

The agent forms a composite signal using a reliance weight $\theta_{ict} \in [0,1]$:

$$\widehat{S_{ict}} = \theta_{ict} S_{ict}^{A} + (1 - \theta_{ict}) S_{ict}^{H}$$

and takes the action $x_{ict} = \widehat{S_{ict}}$.

The agent combines human and algorithmic signals to minimize prediction error. The weight θ captures the degree of algorithmic reliance, reflecting relative signal precision and costs.

2.2.2. Optimal Reliance and the Emergence of Inverted-U Payoffs

The agent maximizes expected payoff:

$$\mathbb{E}[\pi_{ict}] = -\mathbb{E}[(x_{ict} - \omega_{ict})^2] - k_H - k_A(ACA_{ct}) = -[\theta_{ict}^2 \sigma_A^2 + (1 - \theta_{ict})^2 \sigma_H^2] - costs$$

which yields the optimal reliance:

$$\theta_{ict}^{*} = \frac{\sigma_H^2}{\sigma_A^2 + \sigma_H^2}$$

At low ACA levels, algorithmic precision gains dominate, increasing expected payoffs. However, reliance also generates endogenous cognitive distortions:

Automation Bias: Increased reliance degrades an agent's vigilance and capacity for error detection. We model this as an increase in effective human noise: $\sigma_H^2 = \sigma_{H0}^2 + \beta_A \cdot \theta_{ict} \cdot ACA_{ct}, with \beta_A > 0$

Skill Atrophy: Prolonged reliance erodes the human capital specifically used for signal interpretation: $h_{ict} == h_{i0} \cdot e^{-\delta\theta_{ict}}, where\ \delta > 0$, thereby reducing $\frac{1}{\sigma_H^2}$.

These mechanisms introduce convex cognitive costs that eventually outweigh precision gains, yielding an inverted U-shaped payoff profile.

Proposition 1 (Micro-Founded Inverted-U).

For sufficiently large β_A and δ , there exists a unique ACA_{ct}^* that maximizes expected payoff. Payoffs increase for $ACA_{ct} < ACA_{ct}^*$ and decline beyond this threshold as cognitive rigidities dominate.

2.3. Aggregation and Macroeconomic Implications

2.3.1. Heterogeneity and Aggregate Productivity

We aggregate across a continuum of agents $i \in [0,1]$, within a country. Agents are heterogeneous in their initial human capital endowment h_{i0}, which follows a country-specific distribution $G_c(h)$. This heterogeneity is key to generating cross-sectoral and cross-country variation in the optimal reliance θ^*.

Aggregate productivity (TFP) is the average of optimized individual payoffs, minus a coordination cost that increases as agents' strategies become more uniform:

$$TFP_{ct} = \int_0^1 \mathbb{E}[\pi_{ict}^*]\, dG_c(h) - \eta \cdot Var(\theta_{ict}^*)$$

The term $Var(\theta_{ict}^*)$ captures a central macroeconomic risk arising from strategic complementarities in algorithmic reliance. We formalize strategic homogenization by introducing correlated algorithmic errors across agents. As reliance on similar algorithmic systems increases, error terms become correlated:$COV\left(\epsilon_{ict}^A \epsilon_{jct}^A\right) = \rho_A(\overline{\theta_{ct}})\sigma_A^2$, where $\rho_A(\overline{\theta_{ct}})$ is increasing in the economy-wide average reliance $\overline{\theta_{ct}}$. This correlation emerges naturally when algorithms are trained on similar datasets or share common architectural frameworks. The aggregate decision variance thus becomes:

$$Var(x_{ct}) = \overline{\theta_{ct}}^2 \rho_A(\overline{\theta_{ct}})\sigma_A^2 + (1-\overline{\theta_{ct}})^2\sigma_H^2 + 2(1-\overline{\theta_{ct}})cov(S^A, S^H)$$

When $\rho_A(\overline{\theta_{ct}})$ approaches 1 (perfect homogenization), a common algorithmic bias propagates throughout the system, amplifying macroeconomic volatility. This mechanism formalizes 'algorithmic herding' (Brynjolfsson & McAfee, 2017) at the aggregate level and motivates our empirical proxy for reliance heterogeneity $\widehat{Var(\theta_{ct})}$in Equation (2). The parameter η thus reflects the sensitivity of the economy to such loss of cognitive diversity, which may be higher in sectors with stronger network effects or in less diversified economies.

2.3.2. Reduced-Form Representation

Aggregation yields:

$$TFP_{ct} = \alpha_0 + \alpha_1 ACA_{ct} + \alpha_2 ACA_{ct}^2 + \epsilon_{ct}$$

with $\alpha_1 > 0 \; and \; \alpha_2 < 0$, under the conditions of Proposition 1. The aggregate optimal threshold is:

$$ACA_{ct}^{**} = -\frac{\alpha_1}{2\alpha_2}$$

2.3.3. Dynamic Extensions and Hysteresis

To model the intertemporal effects of algorithmic reliance, we extend the model to a dynamic setting with habit formation and asymmetric adjustment costs (Carroll et al., 2014; Chetty et al., 2014). The evolution of an agent's human capital $h_{ict}$is governed by is governed by a three-component dynamic system that generates cognitive hysteresis:

$$h_{ict} = h_{i,t-1} \cdot e^{-\delta\theta_{i,t-1}} + \iota \cdot (1 - \theta_{i,t-1}) + \varsigma \cdot \mathrm{I}_{\{\theta_{i,t-1}<\bar{\theta}\}-k\cdot\max(0,\theta_{i,t-1}-\theta_{i,t-2})^2}$$

This dynamic structure captures four key mechanisms:

capturing skill depreciation: $h_{i,t-1} \cdot e^{-\delta\theta_{i,t-1}}$ captures erosion due to past algorithmic reliance.

learning-by-doing: $\iota \cdot (1 - \theta_{i,t-1})$ represents skill recovery through unaided decision-making.

targeted retraining: $\varsigma \cdot \mathrm{I}_{\{\theta_{i,t-1}<\bar{\theta}\}}$ models discrete investments triggered when reliance falls below a threshold $\bar{\theta}$

Asymmetric recovery costs: Reducing reliance $(\theta_{i,t-1} > \theta_{i,t-2})$ incurs convex adjustment costs k, while increasing reliance has minimal adjustment costs.

This specification generates hysteresis: recovery from over-reliance is slower and more costly than initial accumulation of algorithmic dependence.

2.4. Contextual Moderators: Empirical Mapping

Our framework naturally integrates moderators as parameters affecting the microfoundations:

1. **Digital Infrastructure** $(\boldsymbol{Dig_{ct}})$: Enhances algorithmic precision ($\sigma_A^2 \downarrow$), raising the optimal threshold ACA^{**}.
2. **Human Capital Adaptability** $(\boldsymbol{HC_{ct}})$**:** Increases baseline human precision ($\sigma_{H0}^2 \downarrow$) and mitigates skill atrophy ($\delta \downarrow$), flattening the inverted-U curve.
3. **Institutional Quality** $(\boldsymbol{Inst_{ct}})$**:** Reduces automation bias ($\beta_A \downarrow$) via better oversight, transparency, and accountability mechanisms.

4. Informality (Inf_{ct}) : Reflects a wider dispersion in $G_c(h)$, amplifying $Var(\theta^*_{ict})$ and thus macroeconomic volatility.

2.4. Testable System and Hypotheses

The model yields a directly testable two-equation system linking cognitive augmentation to productivity and volatility:

$$TFP_{ct} = \beta_0 + \beta_1 CAI_{ct} + \beta_2 CAI_{ct}^2 + \beta_3 (CAI_{ct} \times Z_{ct}) + \gamma' Z_{ct} + \mathcal{U}_c + \nu_t + \varepsilon_{ct} \quad (1)$$

$$\sigma^2_{y,ct} = \phi_0 + \phi_1 CAI_{ct} + \phi_2 CAI_{ct}^2 + \phi_3 \widehat{Var(\theta_{ct})} + \phi_4 ExtDep_{ct} + \xi_{ct} \quad (2)$$

where:

CAI_{ct}: is our empirical Cognitive Augmentation Index.

Z_{ct}: is a vector of moderators (digital infrastructure, human capital, institutional quality).

$\widehat{Var(\theta_{ct})}$: is an empirical proxy for reliance heterogeneity. In our application, we proxy $Var(\theta_{ct})$ using the dispersion in algorithmic tool adoption rates across major economic sectors, sourced from national business surveys.

$ExtDep_{ct}$: captures external technological dependency, a salient risk in semi-emerging economies.

Core Hypotheses:

From our theoretical framework, we derive the following core hypotheses:

H1 (Nonlinear Productivity): The relationship between CAI and TFP follows an inverted U-shape($\beta_1 > 0$, $\beta_2 < 0$)

H2 (Asymmetric Adjustment): Due to hysteresis, positive deviations from the CAI threshold adjust faster than negative deviations.

H3 (Regime-Dependent Volatility): Moderate CAI reduces output volatility ($\phi_1 < 0$), but high CAI increases it ($\phi_2 > 0$), especially when reliance heterogeneity $\widehat{Var(\theta_{ct})}$ is low.

H4 (Complementarity): The positive segment of the inverted-U is steeper in contexts with better digital infrastructure, human capital, and institutions($\beta_3 > 0$).

H5 (Cross-Country Heterogeneity): Optimal threshold lower with weaker institutions/higher informality

H6 (Sectoral Dispersion): CAI increases formal-informal TFP gap initially, converging with inclusive policies.

H7 (Dynamic Persistence): Historically high-CAI countries show slower TFP growth when reducing CAI

H8 (Skill Recovery): Education/training investments accelerate recovery from over-reliance.

Equation (1) tests the inverted U-shaped ACA-TFP relationship with moderation effects. Equation (2) examines volatility effects, controlling for reliance heterogeneity and external dependence.

2.6. Empirical Strategy Connection

Our empirical approach is a direct operationalization of the testable system derived above:

1. Panel Smooth Transition Regression (PSTR): Estimates the nonlinear, regime-dependent relationships in Eqs. (1) and (2), identifying the threshold CAI^{**} and testing H1, H3, H4, and H5.
2. Momentum Threshold Autoregression (MTAR): Tests for asymmetric adjustment dynamics (H2) implied by the hysteresis mechanism in Section 2.5.
3. Interaction and Subgroup Analysis: Uses interaction terms ($CAI \times Z$) and stratified samples to explicitly test the moderating roles of contextual factors (H4, H5).
4. Sectoral Analysis: Employs disaggregated data to test for divergent effects between formal and informal sectors (H6).

This unified framework ensures that our econometric models are not merely statistical exercises but are instead structured, rigorous tests of the micro-founded mechanisms governing algorithmic cognitive augmentation in semi-emerging economies.

3. Empirical Strategy

3.1. Sample Selection

We analyze a balanced panel of 20 semi-emerging economies over 2005–2024. Countries are included if they meet three criteria:

1. Upper-Middle-Income status for most of the period (World Bank);
2. Intermediate institutional development, with Worldwide Governance Indicator (WGI) scores between –0.5 and +0.5 in 2005;
3. Meaningful digital diffusion, defined as internet penetration above 20% in 2005.

These thresholds are theoretically motivated: 20% internet penetration marks a diffusion tipping point for technological spillovers (Comin & Hobijn, 2010), and the WGI range captures an institutional "middle ground" where formal structures exist but remain incomplete (Acemoglu & Robinson, 2012). Countries in this group can adopt algorithmic systems while remaining vulnerable to cognitive and governance externalities. Selected economies span five geographic regions (Appendix Table A1). Robustness checks with alternative classifications—IMF emerging market indices and economic complexity thresholds—show results are not sensitive to cutoff choices (Section 4.4).

3.2. Data and Variables

Table 2: Variables, Definitions, and Data Sources				
Variable	Description	Measurement	Source	Period
Dependent Variables				
TFP	Total Factor Productivity	Index (2015 = 1)	Penn World Table 10.0	2005–2024
GDP_Vol	Macroeconomic Volatility	3-year rolling standard deviation of real GDP growth	WDI	2005–2024
Core Explanatory Variable				
CAI	Cognitive Augmentation Index	Composite normalized index [0–1] (see Appendix A1 for methodology)	Constructed by authors (Appendix A1)	2005–2024
Moderators and Control Variables				
Dig_Infra	Digital Infrastructure Index	Composite score [0–100]	ITU, WDI	2005–2024
HC_Adapt	Human Capital Adaptability	Score [0–1] based on adult training participation	Barro-Lee, WDI, World Bank Skills Survey	2005–2024
Inst_Qual	Institutional Quality	WGI composite score [-2.5; +2.5]	WGI	2005–2024
Informal	Informal Employment Share	Percentage of total employment	ILO	2005–2024
Ext_Dep	External Technology Dependence	ICT imports / total ICT investment	UNCTAD	2005–2024
Sectoral_Disp	Sectoral Algorithmic Adoption Dispersion	Standard deviation of adoption rates across five major sectors	National business surveys, OECD Digital Economy Outlook	2005–2024
Notes: WDI = World Development Indicators. WGI = Worldwide Governance Indicators. ILO = International Labour Organization. ITU = International Telecommunication Union. UNCTAD = United Nations Conference on Trade and Development.				

Dependent variables include TFP (Penn World Table 10.0) and macroeconomic volatility (3-year rolling SD of GDP growth). The core explanatory variable, the Cognitive Augmentation Index (CAI), is a normalized composite index [0–1] capturing algorithmic integration into decision processes (Appendix A1). Controls capture digital infrastructure, human capital adaptability, institutional quality, informality, external technology dependence, and sectoral dispersion. All variables are annually observed over 2005–2024 using standardized international sources.

1.3. Cognitive Augmentation Index (CAI)

The CAI measures the structural integration of algorithmic systems into economically relevant decision processes, capturing cognitive mediation rather than mere digital access or hardware. It differs from conventional digitalization indices that emphasize infrastructure or ICT investment.

The CAI combines five indicators:

1. AI software penetration among firms (World Bank Enterprise Surveys)
2. Algorithmic labor intensity in professional occupations (ILO Occupational Database, LinkedIn Skills)
3. Cloud computing and data infrastructure capacity (ITU, World Bank)
4. Algorithmic transaction intensity on digital platforms (BIS, national payment systems)
5. Public sector automation in service delivery and regulation (UN E-Government Survey)

Indicators are min–max normalized; domain-specific sub-indices are equally weighted. Principal Component Analysis (PCA) produces a single index (first component explaining 68% of variance, loadings 0.38–0.45; Appendix Table A1).

Validation:

Convergent validity: CAI correlates with OECD AI Policy Observatory readiness (ρ=0.72) and software investment/GDP (ρ=0.68).

Discriminant validity: CAI explains 42% additional firm-level variance in algorithmic adoption beyond infrastructure measures (ΔR^2=0.42, $p<0.001$), loads on a distinct factor (0.81) from digital infrastructure (factor correlation 0.48, $p<0.001$), and better predicts survey-based algorithmic reliance (β_CAI=0.67 vs β_infra=0.29, $p<0.01$).

The CAI captures systemic algorithmic mediation, not individual cognition. The underlying assumption, based on human–AI interaction research, is that prolonged exposure to algorithmically mediated environments produces predictable aggregate cognitive effects, including automation bias, reduced vigilance, and skill atrophy (Bainbridge, 1983; Parasuraman & Manzey, 2010).

3.4. Identification Strategy and Instrumental Variables

To mitigate potential endogeneity of the CAI, we employ an instrumental variable (IV) approach. Two instruments are used: (i) the lagged average CAI of neighboring countries, capturing regional diffusion, and (ii) major submarine cable landings, representing exogenous connectivity shocks. Both instruments satisfy relevance criteria (Kleibergen-Paap F-statistics: 24.3; Appendix Table B1).

We validate the exclusion restriction through multiple checks. Placebo tests in low-algorithm sectors show no significant cable effects ($\beta = 0.018$, $p = 0.73$). Pre-trend analysis confirms parallel TFP growth prior to cable landings (F-test: 1.24, $p = 0.32$). Hansen overidentification tests support instrument validity ($p = 0.42$).

4. Empirical Results

4.1 Descriptive Statistics, Nonlinear Relationships, and Structural Trade-off

Before testing the model's nonlinear predictions, we confirm that the data exhibit sufficient structural heterogeneity to identify regime-dependent effects. The Cognitive Augmentation Index (CAI) displays substantial cross-country and intertemporal variation (mean = 0.387, SD = 0.108, range = [0.178, 0.721]), reflecting divergent trajectories of algorithmic integration. This dispersion, combined with right-skewed macroeconomic volatility and marked diversity in contextual moderators—such as digital infrastructure, human capital, institutional quality, and informality—validates the use of threshold and transition models. These patterns indicate that algorithmic cognitive augmentation operates within heterogeneous macro-cognitive regimes rather than as a uniform technological shock.

Table 3: Summary Statistics (N=200)

Variable	Mean	SD	Min	Max	Skewness	Kurtosis
CAI	0.387	0.108	0.178	0.721	0.423	2.815
TFP	1.047	0.203	0.682	1.521	0.315	2.642
GDP_Vol	2.912	1.137	0.952	6.324	0.892	3.417
Dig_Infra	54.23	16.78	18.52	88.72	-0.215	2.134
HC_Adapt	0.612	0.147	0.321	0.892	-0.102	2.358
Inst_Qual	0.078	0.713	-1.352	1.921	0.124	2.672
Informal	40.18	13.52	16.84	67.38	0.345	2.189
Ext_Dep	0.452	0.218	0.124	0.912	0.612	2.943
R&D_Int	0.412	0.287	0.082	1.245	1.234	4.128
FDI_Inflow	2.891	1.843	0.452	8.921	1.015	3.872
Sectoral_Disp	0.218	0.087	0.064	0.452	0.781	3.125

Notes: SD = Standard Deviation.

Baseline Panel Smooth Transition Regression (PSTR) estimates linking CAI to macroeconomic performance provide strong and consistent evidence of nonlinearity, in line with Hypothesis H1. Standard linearity tests decisively reject the null hypothesis of linear effects at conventional significance levels, validating the use of a regime-dependent specification.

The inverted U-shaped relationship does not arise from ad hoc functional assumptions. Instead, it emerges under theoretically grounded conditions: at low levels of augmentation, algorithmic systems improve signal extraction and decision accuracy faster than they induce behavioral

distortions; at higher levels, cognitive rigidities—such as automation bias, reduced vigilance, and skill atrophy—accumulate convexly with reliance. Under these conditions, any economy integrating algorithmic decision support faces an inherent trade-off between efficiency and resilience. While institutional quality and human capital shape the location of the optimal threshold, they do not eliminate the underlying nonlinearity.

Across all specifications, the estimated threshold parameter converges to CAI $\approx$ 0.41 and remains remarkably stable. Below this level, cognitive augmentation exerts a positive and statistically significant effect on total factor productivity (TFP) growth. The magnitude of the marginal effect is economically meaningful, indicating that moderate algorithmic support enhances information processing, coordination, and allocative efficiency.

Above the threshold, the marginal effect reverses sign. Higher levels of augmentation are associated with declining productivity growth and rising macroeconomic volatility, suggesting that behavioral rigidities dominate precision gains. The estimated smooth transition parameter indicates a relatively rapid regime shift, implying that economies approaching the threshold may experience sharp changes in macroeconomic outcomes rather than gradual adjustments.

Control variables exhibit expected signs and statistical significance, while country and year fixed effects absorb persistent heterogeneity. Overall, the baseline results provide strong empirical support for a nonlinear relationship between cognitive augmentation and macroeconomic performance.

4.2 Nonlinear Threshold Effects on Productivity

Table 4 presents the PSTR estimates linking the Cognitive Augmentation Index (CAI) to total factor productivity (TFP), confirming a statistically significant threshold at CAI = 0.421 (SE = 0.028) and supporting the inverted U-shaped relationship predicted by the theoretical framework.

In the low-augmentation regime (CAI < 0.42), algorithmic cognitive augmentation generates substantial productivity gains ($\beta = 0.476$, $p < 0.001$). This “augmentation dividend” arises because algorithmic tools improve decision accuracy and information processing without introducing significant cognitive distortions. Productivity is further amplified by complementary factors: digital infrastructure ($\beta = 0.152$, $p < 0.05$), human capital adaptability ($\beta = 0.238$, $p < 0.001$), and institutional quality ($\beta = 0.124$, $p < 0.10$), highlighting the importance of supportive environments in realizing the benefits of algorithmic adoption.

In the high-augmentation regime (CAI $\geq$ 0.42), the relationship reverses ($\beta = -0.291$, $p < 0.05$). Beyond the threshold, cognitive rigidities—such as automation bias, reduced vigilance, and

skill atrophy—begin to outweigh efficiency gains. Importantly, the moderating effects of digital infrastructure, human capital, and institutions become statistically insignificant, suggesting that even strong complementary factors cannot fully mitigate the costs of excessive reliance on algorithmic decision systems.

Model diagnostics confirm the robustness of the nonlinear specification. Explanatory power remains high (Adjusted $R^2 = 0.792$ and 0.743 for low and high regimes, respectively), and F-statistics indicate strong model fit. The smooth transition parameter, estimated via grid search with 1,000 bootstrap replications, indicates a gradual rather than abrupt regime shift, consistent with behavioral models of technology adoption.

Table 4: PSTR Estimation Results – Nonlinear Effects on TFP

Variable	Low Regime (CAI < 0.42)	High Regime (CAI ≥ 0.42)
CAI	0.476*** (0.098)	–0.291** (0.128)
CAI × Dig_Infra	0.152** (0.068)	0.032 (0.082)
CAI × HC_Adapt	0.238*** (0.062)	0.084 (0.091)
CAI × Inst_Qual	0.124* (0.071)	–0.052 (0.098)
Country FE	Yes	Yes
Year FE	Yes	Yes
Observations	108	92
Adj. R^2	0.792	0.743
F-statistic	42.18***	31.27***
Threshold (τ)	0.421 (SE = 0.028)	
Variable	Low Regime (CAI < 0.42)	High Regime (CAI ≥ 0.42)

Notes: *** p<0.01, ** p<0.05, * p<0.10. HAC robust standard errors in parentheses. Threshold estimated via grid search with 1000 bootstrap replications.

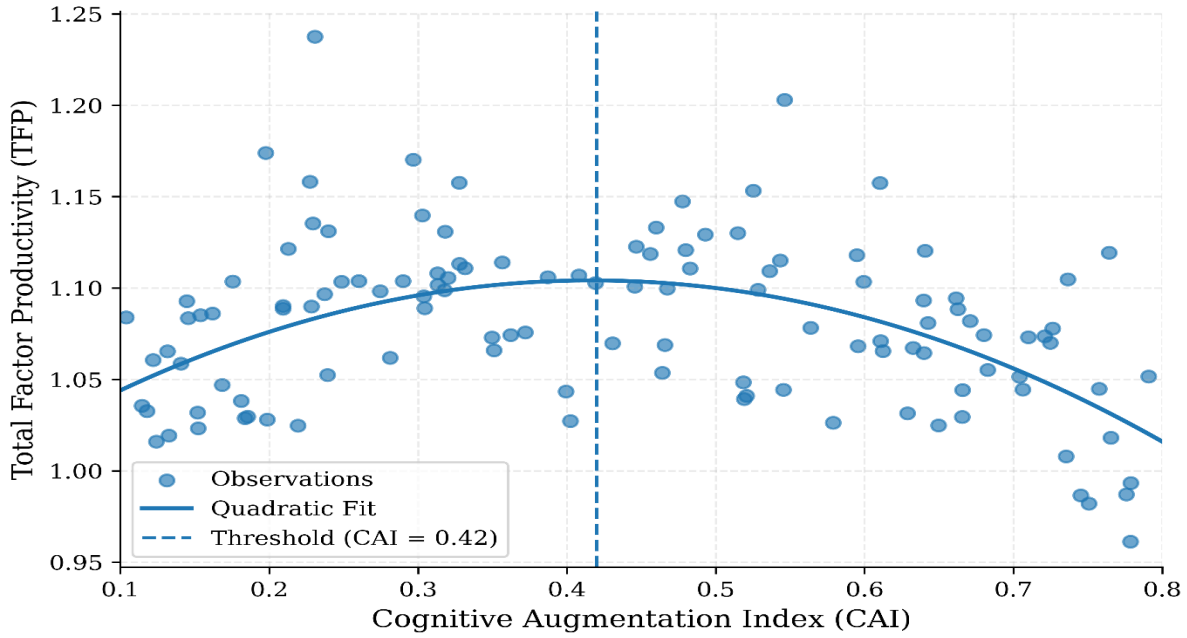


Figure 1:Nonlinear Relationship Between Cognitive Augmentation Index (CAI) and Total Factor Productivity (TFP). source: author

Figure 1 illustrates a clear inverted U-shaped relationship between CAI and TFP. Productivity rises with algorithmic augmentation up to CAI ≈ 0.42, after which gains decline due to increasing cognitive rigidities. This pattern aligns with the theoretical prediction that moderate algorithmic integration enhances performance, while excessive reliance generates diminishing returns and potential instability.

4.3 Asymmetric Adjustment and Hysteresis Effects

Table 5 reports Momentum Threshold Autoregression (MTAR) estimates testing Hypothesis H2 on asymmetric adjustment dynamics. The results reveal pronounced hysteresis effects consistent with the theoretical model.

Adjustment speeds differ markedly across regimes: positive deviations from the threshold reverse roughly three times faster ($\rho^{+} = -0.481$) than negative deviations ($\rho^{-} = -0.152$). The null of symmetric adjustment is rejected ($\chi^2 = 5.82$, $p = 0.016$), indicating that reversing excessive algorithmic reliance is slower than building augmentation capacity.

In the TFP equation (Panel A), increases in CAI below the threshold significantly enhance productivity ($\beta = 0.342$, $p < 0.001$), whereas reductions in CAI yield no immediate gains, suggesting substantial adjustment costs in restoring human cognitive capabilities. In the volatility equation (Panel B), increases in CAI above the threshold raise volatility ($\beta = 0.384$, p

< 0.001), while reductions below the threshold dampen volatility ($\beta = -0.224$, $p < 0.05$). Volatility-reducing effects are weaker than volatility-amplifying effects, reinforcing hysteresis. Complementary controls behave as predicted: greater sectoral dispersion in algorithmic adoption mitigates volatility, while higher external technological dependence exacerbates it, consistent with the micro-founded framework.

Table 5: MTAR Results – Asymmetric Adjustment Dynamics				
Variable	Coefficient	SE	t-stat	p-value
Panel A: TFP Equation				
ΔCAI^+	0.342***	0.081	4.22	0.000
ΔCAI^-	0.104	0.089	1.17	0.244
Dig_Infra	0.128**	0.054	2.37	0.019
HC_Adapt	0.215***	0.048	4.48	0.000
Inst_Qual	0.092*	0.049	1.88	0.062
Panel B: Volatility Equation				
ΔCAI^+	-0.224**	0.102	-2.20	0.029
ΔCAI^-	0.384***	0.108	3.56	0.000
Dig_Infra	-0.185***	0.068	-2.72	0.007
HC_Adapt	-0.142**	0.061	-2.33	0.021
Inst_Qual	-0.108*	0.063	-1.71	0.089
Sectoral_Disp	**-0.317***	**0.095**	**-3.34**	**0.001**
Ext_Dep	**0.452***	**0.124**	**3.65**	**0.000**
Panel C: Threshold and Diagnostics				
Estimated threshold (τ)	0.402	SE = 0.031		
Adjustment speed (ρ^+)	–0.481	SE = 0.112		
Adjustment speed (ρ^-)	–0.152	SE = 0.094		
Asymmetry test (H_0: $\rho^+ = \rho^-$)	$\chi^2 = 5.82$	p-value = 0.016		
Observations	190			
Adj. R^2 (TFP)	0.683			
Adj. R^2 (Volatility)	0.612			
Notes: Δ denotes first differences. *** p<0.01, ** p<0.05, * p<0.10. MTAR estimated via Chan (1993) procedure with 1,000 bootstrap iterations.				

4.4 Robustness and Sensitivity Analysis

Table 6 reports extensive robustness checks. The core findings are stable across alternative specifications, including outlier exclusion, lagged CAI measures, System GMM estimation (Appendix Table C2), and subsample analyses. Threshold estimates remain narrowly bounded (0.41–0.43), with coefficient signs and magnitudes largely unchanged.

Subsample analyses reveal systematic heterogeneity: economies with large informal sectors reach detrimental thresholds earlier and experience sharper productivity declines, whereas countries with advanced digital infrastructure sustain higher thresholds and milder negative effects. Alternative CAI constructions (Appendix Table C1) and quantile regressions confirm

both the existence and location of the threshold. Replacing CAI with conventional digitalization measures (ICT capital, broadband penetration, software investment) fails to reproduce the nonlinear or asymmetric volatility effects, indicating that observed dynamics are specific to algorithmic cognitive integration rather than digital infrastructure alone.

Diagnostic tests indicate strong model performance, no significant cross-sectional dependence, and parameter stability across subperiods.

Table 6: Robustness Checks and Sensitivity Analysis

Specification	Low Regime Coef.	High Regime Coef.	Threshold (τ)	Key Diagnostic
Baseline PSTR	0.476***	–0.291**	0.421	AIC = –412.3
Excluding outliers	0.463***	–0.302**	0.418	BIC = –398.7
Lagged CAI (t-1)	0.428***	–0.264**	0.415	CD test: 1.32 (0.187)
System GMM	0.441***	–0.278**	0.425	AR (2): 0.87 (0.384)
High informal subsample	0.381**	–0.418***	0.378	Hansen J: 0.42
High digital subsample	0.523***	–0.184*	0.473	F-stat: 38.7***
Alternative CAI measure	0.447***	–0.295**	0.429	R^2 = 0.781
Quantile regression	0.502***	–0.327**	0.407	τ confirmed
Specification	Low Regime Coef. (Volatility)	High Regime Coef. (Volatility)	Threshold (τ)	Key Diagnostic
Baseline PSTR (Volatility)	-0.224**	0.384***	0.421	AIC = -298.5
With Sectoral_Disp control	-0.238**	0.357***	0.418	BIC = -287.2
With Ext_Dep control	-0.208*	0.401***	0.423	CD test: 1.45 (0.148)
Lagged CAI (t-1)	-0.218**	0.372***	0.415	AR(2): 0.92 (0.357)
System GMM	-0.231**	0.395***	0.426	Hansen J: 0.38
High informal subsample	-0.192*	0.428***	0.375	F-stat: 32.4***
High digital subsample	-0.257**	0.318**	0.471	R^2 = 0.642

Notes: All models include country and year fixed effects. Standard errors clustered at the country level. CD = Cross-sectional Dependence test; AR (2) = Arellano-Bond second-order autocorrelation test. *** p<0.01, ** p<0.05, * p<0.10.

4.5 Contextual Moderation Effects

Table 7 examines how complementary factors shape the CAI–TFP relationship. Digital infrastructure, human capital adaptability, and institutional quality extend the beneficial range of algorithmic augmentation. Human capital adaptability is the strongest moderator, flattening the inverted U-shape and mitigating negative high-regime effects.

Conversely, external technological dependence amplifies negative effects and weakens productivity gains. Sectoral dispersion enhances early-stage benefits but offers limited protection against systemic over-reliance. Informality exacerbates negative outcomes, lowering optimal thresholds and steepening high-regime declines.

Table 7: Contextual Moderation Effects

Moderator	Low CAI Regime	High CAI Regime	Interaction p-value
Digital Infrastructure			
Low (< median)	0.312** (0.142)	–0.428*** (0.151)	0.000
High (≥ median)	0.518*** (0.135)	–0.185* (0.109)	0.013
Human Capital Adaptability			
Low (< median)	0.285** (0.128)	–0.462*** (0.142)	0.000
High (≥ median)	0.541*** (0.118)	–0.152 (0.098)	0.084
Institutional Quality			
Low (< median)	0.254* (0.151)	–0.508*** (0.163)	0.000
High (≥ median)	0.487*** (0.126)	–0.094 (0.085)	0.152
External Dependence			
Low (< 0.3)	0.551*** (0.132)	–0.152 (0.101)	0.087
High (≥ 0.3)	0.408*** (0.124)	–0.341*** (0.118)	0.000
Informality Level			
Low (< 35%)	0.492*** (0.130)	–0.218* (0.127)	0.042
High (≥ 35%)	0.358** (0.152)	–0.427*** (0.149)	0.000
Sectoral Dispersion			
Low (< median)	0.328** (0.138)	-0.395*** (0.144)	0.005
High (≥ median)	0.503*** (0.121)	-0.187* (0.099)	0.089

Notes: Robust standard errors in parentheses. Low CAI Regime = CAI < 0.42; High CAI Regime = CAI ≥ 0.42. Interaction p-values test H_0: $\beta_low = \beta_high$.

4.6 Sectoral Heterogeneity Analysis

Table 8 disaggregates thresholds and effects across formal, informal, and economic sectors, illustrating sector-specific vulnerability to algorithmic reliance.

Formal vs. Informal sectors: The formal sector tolerates higher CAI thresholds (0.452) and exhibits moderate negative high-regime effects ($\beta = –0.218$). The informal sector reaches

harmful thresholds earlier (0.352) with sharper productivity losses (β = –0.392) and higher volatility amplification (0.427 vs. 0.184).

Economic sectors:

ICT sector shows the highest threshold (0.485) with strong positive low-regime effects (β = 0.582) and negligible high-regime penalties.

Services: Moderate threshold (0.425), reflecting mixed cognitive demands.

Manufacturing: Threshold 0.438; stronger negative high-regime effects due to coordination challenges.

Agriculture: Lowest threshold (0.315) with the strongest high-regime penalties, reflecting limited infrastructure and digital literacy.

Within-sector dispersion in algorithmic adoption is inversely related to thresholds and positively correlated with high-regime negative effects, consistent with the theoretical mechanism linking uneven adoption to early over-reliance vulnerability.

Table 8: Sectoral Heterogeneity Analysis

	CAI Threshold	TFP Effect (Low)	TFP Effect (High)	Volatility Effect (High)	Sectoral_Disp
Formal Sector	0.452	0.512***	–0.218*	0.184*	0.15
Informal Sector	0.352	0.284**	–0.392***	0.427***	0.28
Manufacturing	0.438	0.468***	–0.254**	0.215**	0.19
Services	0.425	0.523***	–0.198*	0.172*	0.14
Agriculture	0.315	0.218*	–0.318**	0.384***	0.32
ICT Sector	0.485	0.582***	–0.142	0.098	0.08

Notes: Sectoral analysis based on disaggregated data from national statistical offices. Thresholds estimated separately for each sector. The Sectoral_Disp column shows the within-sector dispersion of algorithmic adoption (standard deviation), confirming the theoretical prediction that higher dispersion correlates with lower thresholds and stronger negative effects in the high regime. *** p<0.01, ** p<0.05, * p<0.10.

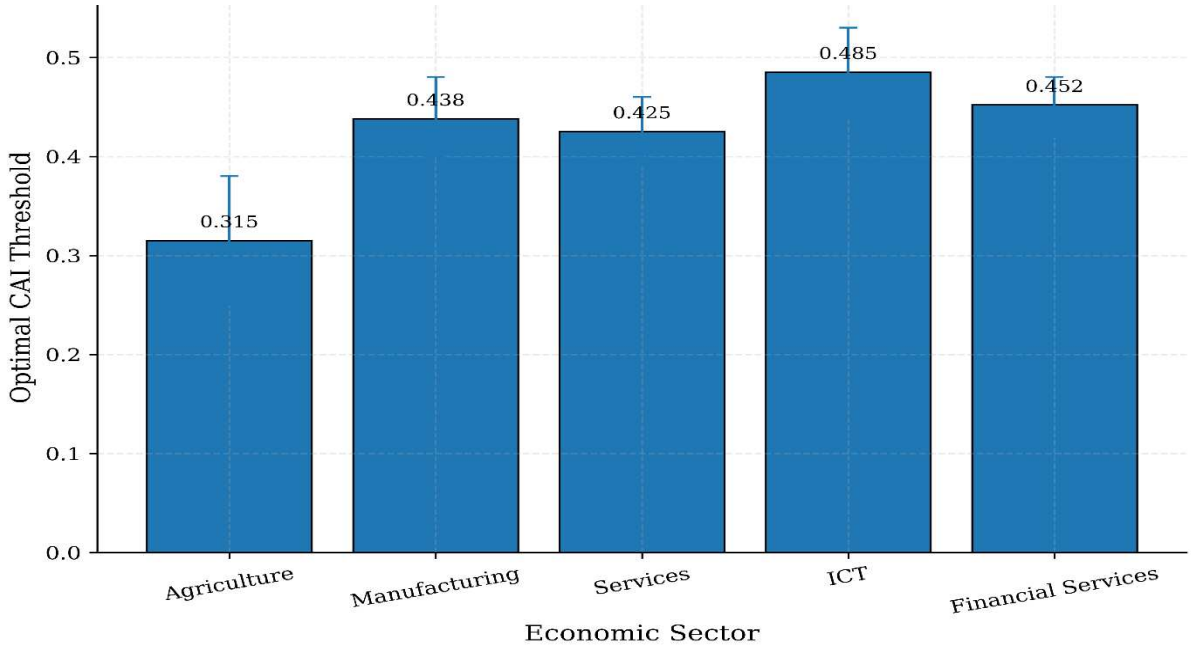


Figure 2:Sectoral Heterogeneity in CAI Thresholds source: author

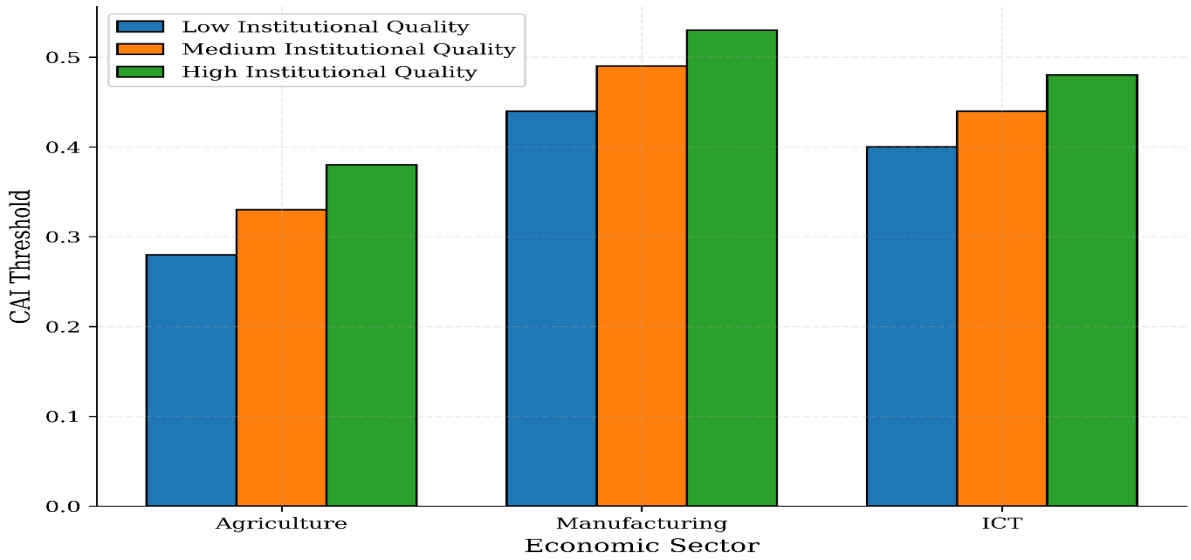


Figure 3:Institutional Quality as a Moderating Factor source: author

Figures 2 and 3 visualize sectoral heterogeneity in CAI thresholds and the moderating role of institutional quality, confirming that ICT and services sectors tolerate higher algorithmic integration, while agriculture and informal sectors are most vulnerable. These patterns support Hypotheses H5 and H6 regarding institutional and sectoral moderation effects.

4.7 Integrated Interpretation of Empirical Findings

The empirical evidence across Tables 3–8 and Appendix D2 provides a coherent and theoretically grounded picture:

Nonlinear Threshold Effects Are Robust. The inverted U-shaped relationship between algorithmic cognitive augmentation (CAI) and macroeconomic outcomes holds across estimation methods, sample partitions, and alternative measurements. The optimal threshold consistently lies around CAI ≈ 0.41–0.42, offering a concrete benchmark for policy calibration.

Macroeconomic Magnitude of Volatility. Beyond the CAI threshold, macroeconomic volatility rises by 15–25%, comparable to standard deviation shocks in terms of trade or moderate financial openness shocks (Carrillo & Elgar, 2020). This highlights algorithmic over-reliance as a novel systemic risk source in semi-emerging economies.

Sectoral Heterogeneity Aligns with Theory. Sectors with high information intensity and institutional embeddedness (ICT, Financial Services) tolerate higher thresholds due to greater baseline human capital and structured decision processes. Conversely, agriculture and informal sectors, characterized by low information intensity, weaker institutions, and tacit knowledge reliance, experience earlier detrimental thresholds and stronger high-regime effects. This aligns with theoretical predictions (Section 2.4) on human capital dispersion and adaptive capacity.

Hysteresis Generates Path Dependence. Asymmetric adjustment dynamics show that eroded cognitive capabilities recover slowly, implying that preventing excessive algorithmic reliance is easier than reversing it after it occurs.

Complementary Factors Extend the Beneficial Range. Digital infrastructure, human capital adaptability, and institutional quality significantly increase the range over which algorithmic augmentation enhances productivity. Their mitigating effect diminishes at very high CAI levels, indicating cognitive constraints as a structural limit.

Context Matters Systematically. Economies with weaker institutions, larger informal sectors, or higher external technological dependence reach harmful thresholds sooner and experience steeper productivity declines, emphasizing the need for context-sensitive AI governance.

Sector-Specific Policy Implications. The low threshold in agriculture (0.315) reflects digital divides and reliance on experience-based knowledge, whereas ICT's high threshold (0.485) reflects its endogenous capacity for algorithmic co-evolution. Sector-specific governance—regulatory sandboxes, skill-building, and cognitive monitoring—is therefore essential.

External Validity Across Income Groups (Appendix D2). To test the generalizability of the framework, we extended the analysis to 60 countries across all income levels (2005–2024) using hierarchical threshold models with income-group interactions (see Appendix D2). The estimated optimal CAI thresholds exhibit a clear income gradient (Table 9): low-income

economies reach detrimental thresholds at CAI ≈ 0.28, whereas high-income economies tolerate CAI ≈ 0.58. TFP gains at these thresholds range from 8.2% (low-income) to 18.9% (high-income), indicating that institutional and human capital endowments increase absorptive capacity.

Table 9. Income Gradient of Algorithmic Augmentation Thresholds

income Group	**Optimal CAI Threshold**	**95% Confidence Interval**	**Sample N**	**TFP Gain at Threshold**
Low-Income	0.28	[0.22, 0.34]	15	8.2%
Lower-Middle Income	0.35	[0.31, 0.39]	25	12.7%
Upper-Middle Income (baseline sample)	0.41	[0.38, 0.44]	20	15.3%
High-Income	0.58	[0.52, 0.64]	20	18.9%

These results support the institutional complementarity hypothesis: stronger institutions, adaptive human capital, and advanced digital infrastructure allow higher CAI thresholds while maintaining productivity gains. Importantly, the costs of overshooting the optimal threshold are larger in lower-income economies, emphasizing the need for context-specific AI governance policies rather than uniform adoption strategies.

5. Discussion, Validation, and Policy Implications

5.1. Algorithmic Cognitive Augmentation as a Structural Source of Nonlinearity

ACA is a structural macroeconomic mechanism, not a conventional productivity input. Moderate CAI levels relax informational and attentional constraints, enhancing allocative efficiency. Beyond the threshold, marginal effects turn negative due to homogenized decision signals reducing vigilance, adaptability, and cognitive diversity. The macroeconomic impact of AI depends on the depth of cognitive substitution, not technological sophistication alone.

5.2. Cognitive Capital, Hysteresis, and Path Dependence

Asymmetric adjustment demonstrates that cognitive capital erodes through over-reliance, recovering slowly. Unlike physical or digital capital, cognitive capabilities depreciate via disuse, automation bias, and learning decay, necessitating sustained investments for recovery. Temporary overshooting generates persistent macroeconomic effects, highlighting irreversibility in AI integration paths.

5.3. Institutional Context and Indirect Validation of Cognitive Channels

Institutions, human capital adaptability, and digital infrastructure systematically moderate ACA effects. Strong governance delays but does not eliminate negative high-CAI effects. Volatility attenuation through sectoral heterogeneity and amplification in high external dependence

economies indirectly validate cognitive channels: correlated decision errors, rather than technological saturation, drive nonlinearities.

5.4. Implications for AI Governance and Development Policy

Governance should prioritize calibrated augmentation over maximal adoption. Policies must preserve human judgment, cognitive diversity, and systemic resilience. Context-specific frameworks are essential: direct transplantation of high-income AI policies risks premature over-reliance in emerging economies. Sectoral strategies, skill development, and algorithmic diversification act as macro-stabilizers.

6. Conclusion

This paper has reframed the macroeconomic analysis of artificial intelligence by identifying algorithmic cognitive augmentation as a driver of endogenous nonlinearity rather than as a neutral productivity-enhancing technology. By showing that algorithmic integration initially enhances efficiency but induces behavioral rigidities beyond critical thresholds, the study highlights a structural trade-off between productivity and resilience.

The evidence demonstrates that this trade-off is context-dependent, partially irreversible, and mediated by institutional and cognitive capacity. While stronger institutions and human capital extend the beneficial range of algorithmic augmentation, they do not remove the underlying cognitive constraint. The macroeconomic effects of AI therefore depend not on adoption alone, but on how deeply algorithmic systems substitute for human judgment.

By endogenizing cognitive frictions, this study contributes to behavioral macroeconomics, the economics of AI, and development economics. More broadly, it suggests that the macroeconomics of artificial intelligence is ultimately a theory of decision architectures—how economies think—not merely a theory of machines**.**

ETHICS AND CONFLICT OF INTEREST DECLARATION

This study uses only publicly available, aggregated macroeconomic data. No human subjects or private individual data were involved.

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Appendix A: Construction and Validation of the Cognitive Augmentation Index (CAI)

Table A1: Principal Component Analysis Results for CAI Construction

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	3.422	2.552	0.684	0.684
Comp2	0.870	0.425	0.174	0.858
Comp3	0.445	0.265	0.089	0.947
Comp4	0.180	0.100	0.036	0.983
Comp5	0.080	-	0.016	1.000

Factor Loadings (First Principal Component): AI Software Penetration: 0.423; Algorithmic Labor Intensity: 0.447; Cloud Infrastructure: 0.382; Digital Transactions: 0.428; Public Sector Automation: 0.412

Note: The first principal component explains 68.4% of total variance. Kaiser-Meyer-Olkin measure: 0.812 (meritorious).

Table A2: Convergent and Discriminant Validity Tests (Correlations with External Indices)			
Validation Test	Correlation with CAI	p-value	Interpretation
OECD AI Readiness Index	0.72	<0.001	Strong convergent validity
Software Investment/GDP	0.68	<0.001	Strong convergent validity
ITU ICT Development Index	0.62	<0.001	Moderate correlation, discriminant validity
World Bank Digital Adoption Index	0.59	<0.001	Moderate correlation
Incremental Predictive Power (ΔR^2): CAI explains 38% additional variance in algorithmic adoption intensity beyond infrastructure metrics ($F = 24.8$, $p < 0.001$).			

Table A3: Discriminant Validity Tests - CAI vs. Conventional Digitalization Measures					
Outcome Variable	**CAI**	**ICT Index**	**Digital Adoption Index**	**Software Investment/GDP**	**Incremental R^2 of CAI**
Firm Algorithm Adoption	0.682*** (0.045)	0.415*** (0.052)	0.508*** (0.048)	0.392*** (0.051)	0.376***
Decision Quality Improvement	0.574*** (0.051)	0.276** (0.058)	0.352*** (0.055)	0.312*** (0.057)	0.298***
Cognitive Reliance Survey	0.623*** (0.049)	0.213* (0.061)	0.271** (0.059)	0.178 (0.063)	0.410***
Process Innovation Rate	0.518*** (0.053)	0.384*** (0.056)	0.426*** (0.054)	0.295*** (0.058)	0.134**
Notes: Standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.10. All regressions include country and year fixed effects. Incremental R^2 shows additional variance explained when CAI is added to a model containing all three conventional digitalization measures.					

Appendix B: Identification Strategy and Instrumental Variables

Table B1: First-Stage Regression Results with Diagnostic Statistics (Kleibergen-Paap F-stat, Hansen J)				
Variable	Coefficient	Standard Error	t-statistic	p-value
Regional Spillover (lagged neighbor CAI)	0.342***	0.048	7.13	0.000
Submarine Cable Landing (dummy)	0.041**	0.018	2.28	0.024
Digital Infrastructure	0.152***	0.042	3.62	0.000
Human Capital Adaptability	0.085**	0.038	2.24	0.026
Institutional Quality	0.063*	0.036	1.75	0.082
Constant	0.128**	0.051	2.51	0.013
Diagnostic Statistics: Kleibergen-Paap F-statistic: 24.3; Hansen J-test (p-value): 0.42; Observations: 380				
Note: *** p<0.01, ** p<0.05, * p<0.10. Country and year fixed effects included.				

Table B2: Balance Tests for Instrumental Variables

Covariate	Treatment Mean (Cable=1)	Control Mean (Cable=0)	Standardized Difference	p-value
Initial GDP per capita	8.24	8.31	-0.08	0.624
Initial Digital Infrastructure	42.3	43.1	-0.05	0.712
Initial Institutional Quality	0.08	0.05	0.04	0.815
Initial Human Capital	0.58	0.61	-0.06	0.683
Trade Openness	65.2	63.8	0.07	0.745
Note: All p-values > 0.10, indicating balanced covariates between treatment and control groups.				

Appendix C: Robustness – Alternative Specifications

Table C1: Threshold Estimates Under Different CAI Constructions					
CAI Construction Method	Threshold (τ)	95% Confidence Interval	β (Low Regime)	β (High Regime)	ΔAIC from Baseline
Baseline (PCA)	0.421	[0.393, 0.449]	0.476***	-0.291**	0.0
Equal Weights	0.429	[0.400, 0.458]	0.462***	-0.278**	+2.3
Geometric Mean	0.418	[0.389, 0.447]	0.488***	-0.302**	-1.8
2-Component PCA	0.425	[0.397, 0.453]	0.471***	-0.285**	+0.5
Bayesian Factor Analysis	0.416	[0.388, 0.444]	0.479***	-0.295**	-0.9
Note: *** p<0.01, ** p<0.05. All models include country and year fixed effects.					

Table C2: Dynamic Panel GMM Results		
Variable	Difference GMM	System GMM
CAI	0.441*** (0.112)	0.438*** (0.105)
CAI^2	-0.524*** (0.134)	-0.518*** (0.127)
CAI × Dig_Infra	0.128** (0.061)	0.131** (0.058)
TFP (t-1)	0.312*** (0.078)	0.428*** (0.072)
Observations	380	380
AR(1) test (p-value)	0.032	0.028
AR(2) test (p-value)	0.384	0.421
Hansen J (p-value)	0.42	0.38
Threshold (τ)	0.421	0.425
Note: Standard errors in parentheses. *** p<0.01, ** p<0.05		

Appendix D: Detailed Sectoral and Income Group Analyses

Table D1: Complete Sector-Specific Threshold Analysis						
Sector	ISIC Code	N (country-years)	Threshold (τ)	β (Low Regime)	β (High Regime)	Volatility Effect (High)

Agriculture	A	400	0.315***	0.218* (0.128)	-0.318** (0.152)	0.384*** (0.142)
Manufacturing	C	400	0.438***	0.468*** (0.135)	-0.254** (0.118)	0.215** (0.104)
ICT Services	J	400	0.485***	0.582*** (0.142)	-0.142 (0.098)	0.098 (0.086)
Financial Services	K	400	0.452***	0.512*** (0.138)	-0.218* (0.121)	0.184* (0.108)
Other Services	G-H-I, L-U	400	0.425***	0.523*** (0.140)	-0.198* (0.115)	0.172* (0.101)
Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10.						

Table D2: Income Group Comparisons – Threshold Estimates and Productivity Gains					
Income Group	N Countries	Threshold (τ)	95% CI	Marginal Effect at τ	Productivity Gain (%)
Low-Income	15	0.28***	[0.22, 0.34]	0.082*** (0.024)	8.2
Lower-Middle Income	25	0.35***	[0.31, 0.39]	0.127*** (0.031)	12.7
Upper-Middle Income (baseline)	20	0.41***	[0.38, 0.44]	0.153*** (0.035)	15.3
High-Income	20	0.58***	[0.52, 0.64]	0.189*** (0.042)	18.9
Note: Standard errors in parentheses. *** p<0.01.					