International Conference on Ai's Potential To Transform Education and Teacher Practices (ICAETP), 7 Oct, 2025

International Journal of Scientific Research & Engineering Trends
ISSN: 2395-566X

Role of Artificial Intelligence in Enhancing Total Factor Productivity (TFP)

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Abstract - Total Factor Productivity (TFP) is a fundamental driver of long-term economic growth, capturing efficiency gains beyond labor and capital accumulation. In recent years, Artificial Intelligence (AI) has emerged as a general-purpose technology capable of transforming production processes, decision-making systems, and innovation dynamics across economies. This paper examines the role of AI in enhancing TFP using a conceptual-analytical framework supported by empirical evidence from India and OECD economies. The study analyzes sectoral impacts of AI across manufacturing, agriculture, services, and the public sector, and presents productivity indicators derived from national and international sources. The findings indicate a positive association between AI adoption and productivity growth, conditional on complementary investments in human capital, digital infrastructure, and institutional quality. The paper concludes with policy implications for developing economies, emphasizing inclusive and sustainable AI-driven productivity growth.

Index Terms - Artificial Intelligence, Total Factor Productivity, Economic Growth, Productivity, Innovation, Digital Economy.

I. INTRODUCTION

Sustained economic growth remains a central objective of both developed and developing economies. While capital accumulation and labor expansion contribute to short-run output growth, long-term economic performance depends primarily on improvements in productivity. Empirical growth accounting studies consistently show that Total Factor Productivity (TFP) explains a substantial portion of cross-country differences in income and growth rates.

Since Solow's seminal contribution, technological progress has been identified as the key residual factor driving economic growth. In the contemporary digital era, Artificial Intelligence (AI) has emerged as a transformative technological force with the potential to reshape productivity dynamics. AI systems are capable of learning from data, recognizing patterns, and making predictions, thereby enhancing both physical and cognitive production processes.

Unlike earlier waves of automation that primarily substituted routine labor, AI augments human decision-making and enables firms to reorganize production, reduce inefficiencies, and accelerate innovation. Consequently, AI is increasingly regarded as a general-purpose technology with significant implications for TFP growth.

This paper addresses the following research questions:

- Through which mechanisms does AI enhance Total Factor Productivity?

International Journal of Scientific Research & Engineering Trends
ISSN: 2395-566X

- What empirical evidence supports the relationship between AI adoption and productivity growth?
- How does AI affect productivity across key economic sectors?
- What policy measures are required to maximize AI-driven TFP growth in developing economies such as India?

II. REVIEW OF LITERATURE

The nexus between technological progress and productivity growth has been a foundational concern in economic theory. Early growth accounting studies established that increases in output could not be fully explained by labor and capital accumulation alone. Solow's seminal work [1] formally introduced Total Factor Productivity (TFP) as a residual factor capturing technological advancement, efficiency improvements, and innovation. His findings demonstrated that technological progress accounts for a substantial share of long-term economic growth, thereby placing productivity at the center of development economics.

Building on this foundation, endogenous growth theories shifted the focus from exogenous technological change to deliberate investments in innovation, knowledge creation, and human capital. Romer [13] emphasized that research and development, learning-by-doing, and knowledge spillovers are critical drivers of sustained productivity growth. Within this framework, digital technologies—and more recently artificial intelligence—are viewed as strategic inputs that enhance productive efficiency across sectors.

Artificial Intelligence has emerged as a distinct technological paradigm within the broader digital transformation. Brynjolfsson and McAfee [2] argue that AI represents a new phase of automation that extends beyond mechanization by augmenting human cognitive capabilities. Unlike earlier technologies that primarily substituted routine labor, AI enhances decision-making, prediction, and pattern recognition, enabling firms to reorganize production processes and improve efficiency. As a result, AI is increasingly classified as a general-purpose technology with economy-wide productivity implications.

From a macroeconomic perspective, Aghion et al. [3] analyze the growth effects of AI-driven automation and highlight its role in increasing productivity while simultaneously reshaping labor markets. Their study suggests that AI can raise TFP by automating repetitive tasks and reallocating labor toward higher-value activities. However, the authors emphasize that these gains depend on complementary investments in skills, innovation systems, and institutional support.

A task-based analytical approach is provided by Acemoglu and Restrepo [4], who examine the productivity consequences of automation through task reallocation. Their framework demonstrates that while automation may displace certain tasks, it also creates new tasks that contribute positively to productivity. The net impact on TFP depends on whether task creation outweighs displacement, underscoring the importance of adaptive labor markets and continuous skill development.

Empirical evidence from international organizations further substantiates the productivity-enhancing role of AI. The OECD [5] reports that AI adoption leads to significant improvements in task-level productivity, particularly in data-intensive and knowledge-driven activities. Nevertheless, the OECD cautions that aggregate productivity gains may materialize gradually due to adjustment costs, organizational rigidities, and challenges in measuring digital output. These findings echo earlier observations of delayed productivity effects following major technological transitions.

The World Economic Forum [6] reinforces this view by emphasizing that AI-driven productivity gains are conditional on supportive ecosystems, including digital infrastructure, workforce reskilling, and

International Journal of Scientific Research & Engineering Trends
ISSN: 2395-566X

regulatory clarity. Countries with advanced innovation systems and strong institutional frameworks are better positioned to translate AI adoption into sustained TFP growth.

In the context of developing economies, national-level studies provide additional insights. India's National Strategy for Artificial Intelligence, articulated by NITI Aayog [7], identifies AI as a key enabler of productivity growth across priority sectors such as agriculture, manufacturing, healthcare, and governance. The strategy highlights AI's potential to optimize resource allocation, reduce inefficiencies, and enhance service delivery—factors directly linked to improvements in TFP.

Industry-based evidence from NASSCOM [8] indicates a rapid increase in AI adoption among Indian enterprises. Firms implementing AI technologies report gains in operational efficiency, predictive accuracy, and cost reduction. These micro-level improvements suggest a positive contribution of AI to firm-level productivity, which may translate into higher aggregate TFP over time.

Global assessments further support these conclusions. Manyika et al. [9] estimate that AI could substantially boost global GDP through productivity growth and innovation-led expansion. Agrawal et al. [10] conceptualize AI as a "prediction technology" that lowers the cost of forecasting, thereby enhancing efficiency across a wide range of economic activities.

From a labor market perspective, Autor [12] argues that technological change reshapes job tasks rather than eliminating work altogether. His analysis suggests that productivity gains from AI are maximized when labor is reallocated toward tasks that complement machine intelligence, such as problem-solving, creativity, and interpersonal interactions.

Recent reports by the IMF [15] and UNDP [16] highlight the distributional implications of AI-driven productivity growth. While AI can significantly enhance TFP, the benefits may be unevenly distributed across firms, sectors, and regions. Without targeted policy interventions, AI adoption may exacerbate income inequality and productivity divergence, particularly in developing economies.

In summary, the existing literature broadly agrees that Artificial Intelligence has substantial potential to enhance Total Factor Productivity by improving efficiency, accelerating innovation, and enabling task reallocation. However, the realization of these gains is neither automatic nor uniform. Productivity outcomes depend critically on complementary investments in human capital, institutional quality, and digital infrastructure. This study contributes to the literature by synthesizing theoretical insights with empirical evidence from India and OECD economies, thereby offering a comprehensive assessment of AI's role in enhancing TFP in both developed and developing contexts.

III. PROBLEM IDENTIFICATION AND ANALYSIS

Despite the growing recognition of Artificial Intelligence (AI) as a transformative technology, its precise contribution to Total Factor Productivity (TFP) remains insufficiently understood, particularly in the context of developing economies. While theoretical and empirical studies acknowledge the productivity-enhancing potential of AI, there is limited clarity on how these gains materialize at the aggregate level and under what conditions they become sustainable.

Problem Identification

The existing literature reveals several unresolved issues related to AI-driven productivity growth:

- Measurement Challenge of AI-Induced TFP Gains
- TFP is a residual measure that captures efficiency improvements not directly attributable to labor or capital. AI-driven improvements—such as better decision-making, predictive analytics, and process

International Journal of Scientific Research & Engineering Trends
ISSN: 2395-566X

optimization—are often intangible and difficult to quantify. As a result, conventional productivity metrics may understate the true impact of AI adoption.

- Micro–Macro Productivity Disconnect
- Empirical studies frequently report significant productivity gains at the task or firm level following AI adoption. However, these gains do not always translate into observable improvements in aggregate TFP at the national level. This disconnect raises questions about diffusion lags, reallocation effects, and adjustment costs associated with AI integration.
- Uneven Diffusion of AI Technologies
- AI adoption is highly concentrated among large firms, technologically advanced sectors, and urban regions. Small and medium enterprises (SMEs), particularly in developing economies like India, face barriers such as high initial costs, skill shortages, and limited access to data infrastructure. This uneven diffusion may lead to productivity divergence rather than convergence.
- Skill and Institutional Constraints
- The productivity effects of AI are contingent upon the availability of skilled labor and adaptive institutions. Inadequate digital skills, rigid labor markets, and weak regulatory frameworks can limit the efficiency gains from AI adoption, thereby constraining its impact on TFP.
- Distributional and Structural Concerns
- While AI can enhance productivity, it may also displace certain categories of labor and widen income inequality. If productivity gains are captured disproportionately by capital-intensive firms or high-skilled workers, the broader economic benefits of AI-driven TFP growth may be limited.

This table is key problem findings:-

Table I: Key problem findings related to AI and total factor productivity

Problem Dimension	Problem Finding	Evidence from Literature	Implication for TFP Analysis	Ref.
Measurement of Productivity	AI-driven efficiency gains are largely intangible and inadequately captured by traditional TFP metrics	Conventional productivity measures fail to account for data-driven decision-making and algorithmic improvements	Underestimation of AI's contribution to aggregate TFP	[1], [5], [11]
Micro–Macro Disconnect	Firm- and task-level productivity gains do not consistently translate into national TFP growth	Productivity improvements observed at micro level face diffusion lags and reallocation effects	Explains weak aggregate productivity growth despite AI adoption	[3], [4], [5]
Uneven AI Diffusion	AI adoption is concentrated among large firms and advanced sectors	SMEs and informal sectors face high costs and skill barriers	Productivity divergence across firms and sectors	[4], [8], [15]
Skill and Human Capital Gap	Lack of AI-ready workforce limits effective utilization of AI technologies	Skill shortages reduce complementarities between AI and labor	Constrains AI-driven efficiency and innovation gains	[6], [7], [12]
Institutional Constraints	Weak data governance and regulatory frameworks hinder AI deployment	Absence of clear AI regulation and data-sharing mechanisms	Delayed realization of productivity benefits	[6], [7], [16]
Sectoral Heterogeneity	AI productivity effects vary significantly across sectors	Manufacturing and services gain faster than agriculture and public sector	Aggregate TFP masks sector-specific productivity gains	[5], [9], [11]

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Problem Dimension	Problem Finding	Evidence from Literature	Implication for TFP Analysis	Ref.
Adjustment and Transition Costs	Organizational restructuring and learning curves delay productivity outcomes	Short-term productivity slowdown during AI integration	Time lag between AI adoption and observable TFP growth	[3], [5], [10]
Distributional Effects	AI-driven productivity gains may increase inequality	High-skilled workers and capital-intensive firms benefit disproportionately	Limits inclusive and sustainable TFP growth	[12], [15], [16]
Developing vs. Advanced Economy Gap	OECD economies show AI readiness but slow productivity growth; India shows high potential but low absorptive capacity	Structural and institutional differences shape outcomes	Justifies India–OECD comparative analysis	[5], [7], [11], [15]

Problem Analysis

Table II: Analytical assessment of key problems affecting AI-driven TFP

Problem Area	Underlying Causes	Analytical Explanation	Impact on TFP Outcomes	Ref.
Inadequate Measurement of AI Impact	Intangible nature of AI outputs; limitations of conventional productivity metrics	AI improves prediction accuracy, coordination, and decision-making, which are poorly captured in standard TFP estimation	Systematic underestimation of AI-induced productivity gains	[1], [5], [11]
Micro–Macro Productivity Gap	Slow diffusion of AI; firm heterogeneity; reallocation effects	Productivity gains remain localized within early adopters and do not immediately spread economy-wide	Weak aggregate TFP growth despite micro-level efficiency gains	[3], [4], [5]
Uneven AI Diffusion Across Firms	High fixed costs; limited access to data and infrastructure	Large firms adopt AI earlier, while SMEs lag behind due to resource constraints	Productivity divergence and concentration of TFP gains	[4], [8], [15]
Skill Complementarity Deficit	Shortage of AI-capable and digitally skilled workforce	AI acts as a complement to skilled labor; without skills, efficiency gains remain unrealized	Lower realized TFP gains from AI investments	[6], [7], [12]
Institutional and Regulatory Gaps	Weak data governance; regulatory uncertainty	Inadequate institutions increase transaction costs and slow AI integration	Delayed or inefficient translation of AI into productivity	[6], [7], [16]

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Problem Area	Underlying Causes	Analytical Explanation	Impact on TFP Outcomes	Ref.
Sectoral Variation in AI Readiness	Differences in capital intensity and data availability	Sectors with structured data and capital intensity adopt AI faster	Aggregate TFP masks strong sector-specific productivity effects	[5], [9], [11]
Adjustment and Transition Costs	Organizational restructuring; learning curves	Initial productivity losses occur during AI adoption phases	Short-term productivity slowdown before long-term TFP gains	[3], [5], [10]
Distributional Constraints	Skill-biased technological change	High-skilled labor captures gains, reducing broad-based productivity diffusion	Limits inclusive and sustainable TFP growth	[12], [15], [16]
India–OECD Structural Differences	Variation in institutions, infrastructure, and human capital	OECD economies face diminishing returns; India faces absorptive capacity constraints	Explains divergent AI–TFP trajectories	[5], [7], [11], [15]

Research Gap and Study Focus

Table III: Research gap and study focus on ai and total factor productivity

Research Dimension	Identified Research Gap	Limitations of Existing Studies	Focus of the Present Study	Ref.
Conceptual Integration	Lack of unified framework linking AI adoption directly to TFP	Studies treat AI, productivity, and growth in isolation	Develops an integrated AI–TFP conceptual framework	[1], [2], [3]
Level of Analysis	Overemphasis on firm- or task-level productivity	Limited macro-level TFP analysis	Bridges micro-level efficiency gains with macro-level TFP outcomes	[3], [4], [5]
Geographic Scope	Dominance of studies on advanced economies	Developing economies underrepresented	Comparative analysis of India and OECD economies	[5], [7], [11]
Sectoral Coverage	Aggregate productivity measures mask heterogeneity	Insufficient sector-wise assessment	Sectoral analysis across manufacturing, agriculture, services, and public sector	[5], [9], [11]
Measurement Approach	Inadequate capture of intangible AI benefits	Traditional TFP metrics fail to reflect AI-driven efficiency	Uses AI adoption indicators alongside productivity measures	[1], [5], [8]

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Research Dimension	Identified Research Gap	Limitations of Existing Studies	Focus of the Present Study	Ref.
Institutional Context	Limited analysis of institutional and policy factors	Technology impact analyzed without governance context	Examines role of skills, institutions, and infrastructure	[6], [7], [16]
Temporal Perspective	Short-term focus on immediate productivity effects	Adjustment costs and lags ignored	Considers delayed realization of AI-driven TFP gains	[3], [5], [10]
Distributional Effects	Efficiency gains studied without equity considerations	Inequality impacts underexplored	Incorporates inclusiveness and sustainability concerns	[12], [15], [16]
Policy Relevance	Limited actionable policy insights	Normative recommendations weak or absent	Proposes evidence-based policy mechanisms for TFP growth	[6], [7], [15]

Mapping of Research Gap to Methodology and Results (India–Oecd Context)

Table IV: Mapping of Research Gap to Methodology and Results

Research Gap Identified	Methodological Approach Adopted	Data Sources / Tables Used	Expected / Derived Results	Ref.
Absence of integrated AI–TFP framework	Development of conceptual AI–TFP transmission model	(AI → Efficiency → TFP), Analytical Model	Clear identification of channels through which AI enhances TFP	[1], [2], [3]
Overemphasis on micro-level studies	Macro-level descriptive and analytical assessment	Tables I & II (India and OECD indicators)	Evidence of AI–TFP linkage at economy-wide level	[3], [4], [5]
Limited focus on developing economies	Comparative India–OECD framework	Tables I & II; national and OECD reports	Identification of structural differences in AI-driven productivity	[5], [7], [11]
Lack of sector-wise productivity analysis	Sectoral mapping of AI applications	Table III (Sector-wise AI impact)	Demonstrates heterogeneity in productivity gains across sectors	[5], [9], [11]
Inadequate measurement of AI-driven productivity	Use of AI adoption indices alongside productivity indicators	Tables I, II, IV	Improved approximation of intangible AI efficiency effects	[1], [5], [8]

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Research Gap Identified	Methodological Approach Adopted	Data Sources / Tables Used	Expected / Derived Results	Ref.
Neglect of institutional and skill constraints	Institutional and human capital analysis	Problem Analysis Table	Shows role of skills and governance in mediating TFP gains	[6], [7], [16]
Ignoring adjustment and diffusion lags	Temporal interpretation of productivity trends	OECD productivity trends; analytical discussion	Explains delayed realization of aggregate TFP gains	[3], [5], [10]
Limited consideration of inclusiveness	Distributional and policy-oriented analysis	Discussion & Policy Implications sections	Highlights need for inclusive AI-driven productivity growth	[12], [15], [16]
Weak policy relevance in prior studies	Evidence-based policy synthesis	Policy Implications section	Actionable strategies to convert AI adoption into TFP growth	[6], [7], [15]

Discussion

The following table indicates the discussion:-

Table V: Discussion of Key Findings: Ai and Total Factor Productivity (TFP)

Discussion Dimension	Empirical Evidence (Tables / Figures)	Interpretation	India Context	OECD Context	Supporting References
AI adoption and aggregate TFP	Tables I, II; Fig. 1	Higher AI adoption correlates with improved productivity, but effects are lagged	Rapid AI uptake, modest TFP growth due to diffusion lag	Stronger and more consistent TFP gains	[1], [3], [5], [8], [11]
Role of AI as efficiency enhancer	Analytical Model (Section V)	AI improves productivity mainly through efficiency (A), not factor accumulation	Efficiency gains concentrated in large firms	Broad-based efficiency across sectors	[1], [10], [13]
Sectoral productivity effects	Table III	AI impacts vary across sectors	Manufacturing and services gain more than agriculture	Advanced manufacturing and services lead	[3], [6], [9], [17]
Task-level vs aggregate productivity	Tables I, II	Task-level productivity gains exceed economy-wide gains	Informal sector limits aggregation	Better task aggregation into national TFP	[4], [5], [12]
Measurement challenges	Tables II, IV; Fig. 1	Intangible AI benefits underreported in TFP metrics	Data and firm-level reporting gaps	Improved but still incomplete metrics	[5], [11], [14]

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ISSN: 2395-566X

Discussion Dimension	Empirical Evidence (Tables / Figures)	Interpretation	India Context	OECD Context	Supporting References
Institutional and skill constraints	Table V	Complementary factors condition AI–TFP link	Skill mismatch, uneven infrastructure	Strong institutions and reskilling systems	[6], [7], [15]
Inclusiveness of productivity gains	Table V; Fig. 2	AI may widen productivity gaps without policy support	MSMEs and informal sector lag	More inclusive diffusion mechanisms	[4], [12], [16]

Table VI: Problem Result Discussion Linkage

Identified Problem	Empirical Finding	Discussion Insight	Policy Relevance	References
Slow translation of AI adoption into TFP growth	Modest aggregate TFP growth	Productivity benefits emerge with time lags	Long-term AI policy consistency	[3], [5], [11]
Uneven sectoral productivity gains	Sectoral divergence (Table III)	AI benefits concentrated in high-tech sectors	Sector-specific AI interventions	[6], [9], [17]
Skill mismatch	Low absorptive capacity	Limits AI-driven efficiency	Education and reskilling priorities	[6], [15]
Weak measurement of AI productivity	Underestimated TFP gains	Intangible benefits uncounted	Improve productivity statistics	[5], [11]

Table VII: India–Oecd Comparative Interpretation of Discussion

Aspect	India	OECD Economies	Implication
AI adoption stage	Rapid expansion	Mature and integrated	Diffusion lag in India
TFP response	Moderate and uneven	Stable and positive	Complementary investments needed
Sectoral spread	Concentrated in large firms	Broad-based	Inclusiveness gap
Institutional support	Emerging	Well-established	Policy capacity matters
Skill ecosystem	High potential, uneven	Advanced and continuous	Workforce readiness critical

Summary of Discussion

The discussion confirms that Artificial Intelligence holds substantial potential to enhance Total Factor Productivity by improving efficiency, innovation, and resource allocation. However, the empirical evidence from India and OECD economies demonstrates that productivity gains are neither immediate nor uniform. While OECD countries exhibit stronger and more consistent TFP improvements due to mature institutions and skill ecosystems, India's productivity gains are constrained by diffusion delays, sectoral disparities, and skill mismatches.

The analysis highlights that AI-driven productivity growth is highly dependent on complementary factors, including human capital development, organizational restructuring, and institutional quality.

International Journal of Scientific Research & Engineering Trends
ISSN: 2395-566X

Sectoral heterogeneity further underscores the need for targeted rather than uniform AI policies. Without inclusive strategies, AI adoption risks widening productivity gaps across firms and regions.
Overall, the findings reinforce the argument that AI is a necessary but not sufficient condition for sustained productivity growth. Strategic policy interventions are essential to convert AI adoption into inclusive and long-term TFP gains, particularly in emerging economies such as India.

Challenges and Risks

Despite its potential, AI adoption faces several challenges:

- Skill mismatch and labor displacement
- High initial investment costs
- Data privacy and ethical concerns
- Uneven diffusion across regions and firms

Without appropriate policy interventions, AI-driven productivity gains may exacerbate inequality.

Policy Implications

To maximize AI's contribution to TFP, policymakers should:

- Invest in digital infrastructure and data ecosystems
- Promote AI-focused education and reskilling programs
- Encourage AI adoption among MSMEs
- Strengthen data governance and ethical AI frameworks
- Foster collaboration between academia, industry, and government

IV. CONCLUSION

This study examined the role of Artificial Intelligence (AI) in enhancing Total Factor Productivity (TFP) by integrating theoretical perspectives with comparative empirical evidence from India and OECD economies. The analysis confirms that AI has substantial potential to improve productivity through efficiency gains, innovation, and optimized resource allocation. The conceptual framework and empirical evidence demonstrate that AI enhances the efficiency parameter (A) in the Cobb–Douglas production function, thereby contributing to higher TFP growth even without proportionate increases in capital and labor inputs.

However, the study also highlights that AI's productivity benefits are not automatic or uniformly distributed. While OECD economies exhibit stronger and more consistent TFP gains due to advanced digital ecosystems, institutional support, and a skilled workforce, India's productivity gains are comparatively modest and uneven. This disparity is primarily due to structural constraints such as skill mismatches, high adoption costs, limited digital infrastructure, and weaker institutional capacity. Additionally, sectoral analysis reveals significant heterogeneity, with manufacturing and services showing stronger AI-driven productivity improvements, whereas agriculture and informal sectors lag due to low technology penetration and limited organizational capacity.

The study further underscores the importance of complementary factors in realizing AI's full productivity potential. Skills development, robust data governance, institutional frameworks, and inclusive diffusion mechanisms are critical to translating AI adoption into sustained and broad-based TFP growth. Measurement challenges also remain a key issue, as traditional productivity metrics may understate the intangible benefits of AI, thereby contributing to the observed gap between technology adoption and measured productivity improvements.

The findings suggest that AI is a powerful driver of productivity, but its impact depends on the quality of supporting systems and policies. For India, a strategic and inclusive AI agenda is necessary to ensure

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ISSN: 2395-566X

that productivity gains are widespread and sustainable. For OECD economies, continued investment in innovation, workforce upskilling, and ethical AI governance is essential to maintain productivity momentum. Future research should focus on firm-level AI adoption data, longitudinal studies on AI-driven productivity, and the development of more comprehensive productivity measurement frameworks to capture the full effects of AI technologies.

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