Volume 4 • Issue 2 • September 2025

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GLIMS Journal of Management Review and Transformation

Great Lakes Institute of Management, Gurgaon
mrt.greatlakes.edu.in
Online ISSN: 2583-5076

Online ISSN: 2583-5076

GLIMS Journal of Management Review and Transformation is published biannually in March and September by Great Lakes Institute of Management, Gurgaon.

GLIMS Journal of Management Review and Transformation is hosted on our web-based online submission and peer review system. Please read the Manuscript Submission guidelines on the journal website (https://mrt.greatlakes.edu.in/), and then visit https://peerreview.sagepub.com/mrt to login and submit your article online. Manuscripts should be prepared in accordance with the 7th edition of the *Publication Manual of the American Psychological Association*.

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Abstracting and Indexing: *GLIMS Journal of Management Review and Transformation* is indexed in J-Gate.

Change of Address: Four weeks' advance notice must be given when notifying change of address. Please send the old address label to ensure proper identification. Please specify the name of the journal and send change of address notification to customerservicejournals@sagepub.in

Printed and published by Samiran Baral on behalf of Great Lakes Institute of Management at Great Lakes Institute of Management Gurgaon, Bilaspur-Tauru Road, Bilaspur, Gurugram, Haryana 122413. Printed at Sai Printo Pack Pvt Ltd, A 102/4 Phase II, Okhla Industrial Area, New Delhi, Delhi 110020.

Editor: Preeti Goyal

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About the Journal

The journal is published by Great Lakes Institute of Management, Gurgaon, India. The aim of the journal is to attract articles that address issues the industry is currently facing. A special focus is on articles that provide innovative solutions to these issues. The journal articles not only are of interest to academics, but also, with their focus on relevance, should be of interest to policy makers, think tanks, government, corporate and multilateral institutions, professionals, and industry leaders. Manuscripts undergo a double-blind peer review process, and the journal follows all international journal publication norms. The journal is published with an open-access format so that it reaches the maximum readers. Journal Publishing Services for publication are powered by Sage Spectrum.

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Aims and Scope

GLIMS Journal of Management Review and Transformation aims to publish scientific, empirical research on the theory, practice, and contemporary perspectives of management focusing on the problems, interest, and concerns of managers. It aims to explore interesting questions and phenomena in management, develop and/or test theory, replicate prior studies, and review and synthesize existing research.

Within its scope are all aspects of management related, but not limited, to strategy, entrepreneurship, innovation, information technology, digital business, analytics, artificial intelligence, machine learning, and policy and organizations, as well as all functional areas of business, such as organizational behavior, human resource management, accounting, finance, marketing, operations, data and analytics, and technology transformation.

This journal intends to publish a variety of articles including quantitative and qualitative empirical research articles and conceptual articles that provide novel perspectives on recent business phenomena. To achieve our aim of writing about business transformation, the journal will also include case studies and book review articles. It would also publish abstracts of PhDs that are relevant and in-line with the journal's objectives.

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Editorial

GLIMS Journal of Management
Review and Transformation
4(2) 123, 2025

DOI: 10.1177/jmrt.251400085
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It gives me great pleasure to welcome our readers to Volume 4, Issue 2 of the GLIMS Journal of Management Review and Transformation (JMRT). Since its inception, JMRT has continued to evolve as a credible platform for high-quality research in management and business studies. Our vision remains steadfast, to bridge the gap between theory and practice while advancing scholarship that addresses contemporary challenges faced by organizations and policymakers worldwide.

I am proud to share that, following successful indexing in J-Gate and Google Scholar, JMRT is now also indexed in the EBSCO research database, further enhancing the journal's visibility and accessibility to researchers, academicians, and practitioners worldwide. These milestones reflect the growing recognition of our commitment to academic rigor and impactful research dissemination.

The articles featured in this issue address diverse themes in leadership, strategy, human resources, organizational transformation, and technology-driven change. Each paper contributes unique perspectives and empirical insights that not only enrich academic discourse but also offer actionable implications for decision-makers in business and policy.

I extend my heartfelt appreciation to the authors who entrusted their research to JMRT, and to our dedicated reviewers whose scholarly feedback and professionalism uphold the journal's high standards. Their collective effort ensures that every article we publish meets the expectations of a discerning global readership.

As JMRT continues to expand its academic reach, I invite scholars, practitioners, and doctoral researchers to submit their original work on emerging issues in management and transformation. I look forward to furthering our mission of advancing management thought that is both intellectually rigorous and practically relevant.

Dr. Akhter Mohiuddin Rather
Editor, *GLIMS Journal of Management Review and Transformation*

Conceptual Paper

The Impact of Neurotechnology on Employee Motivation and Workplace Productivity

GLIMS Journal of Management Review and Transformation
4(2) 124–137, 2025

DOI: 10.1177/jmrt.251398084
mrt.greatlakes.edu.in

Triptii Shelkke[1], Divya Rahul Jain[2] and Mallika Singh[2]

Abstract

This research article explores the impact of neurotechnology on employee motivation and workplace productivity. With the growing integration of brain–computer interfaces (BCIs) and neurofeedback in professional settings, this study aims to understand whether these technologies can enhance cognitive performance, emotional regulation and focus—key elements that drive motivation and, in turn, boost productivity. Neurotechnology can positively influence employee motivation by optimising brain activity, ultimately leading to improved workplace performance. This study investigates the impact of neurotechnology—specifically BCIs and neurofeedback—on employee motivation and workplace productivity. Using a qualitative systematic literature review guided by PRISMA 2020, we reviewed 15 peer-reviewed studies published between 1996 and 2025, primarily from Asian contexts. The findings reveal that neurotechnological tools can enhance cognitive performance, emotional regulation and attentional control, thereby positively influencing workplace motivation and productivity. However, ethical concerns regarding data privacy, consent and technostress present significant challenges. The study provides evidence-based recommendations for HR professionals and managers to ethically integrate neurotechnology into employee development strategies while ensuring psychological safety and informed consent.

[1] Thakur Institute of Management Studies & Research, Mumbai, Maharashtra, India
[2] Thakur Global Business School, Mumbai, Maharashtra, India

Corresponding author:
Triptii Shelkke, Thakur Institute of Management Studies & Research, Mumbai, Maharashtra 400101, India.
E-mail: trtgbs@gmail.com

Keywords

Neurotechnology, systematic literature review, PRISMA 2020, brain–computer interface, neurofeedback, motivation–productivity link, HR technology

Submitted 16 May 2025; resived 05 October 2025; accepted 31 October 2025

Introduction

In the modern workplace, the pursuit of higher employee motivation and productivity is more critical than ever. As organisations adapt to rapid technological changes and increasingly competitive environments, they are turning to innovative solutions that promise not only efficiency but also cognitive and emotional optimisation. One such frontier is neurotechnology—a field that integrates neuroscience with advanced technological tools such as brain–computer interfaces (BCIs) and neurofeedback to monitor and enhance brain activity.

While neurotechnology has historically been associated with clinical rehabilitation and assistive applications, its potential use in non-clinical settings such as corporate environments is gaining momentum. Employers are beginning to explore how tools that enhance focus, reduce stress or regulate emotions can lead to better employee engagement and improved decision-making. This shift aligns with the growing interest in organisational cognitive neuroscience, an emerging discipline that seeks to connect brain science with management and organisational behaviour.

Despite these exciting developments, the application of neurotechnology in the workplace remains a relatively underexplored area—both scientifically and ethically. Several critical questions emerge: Can neurotechnological interventions meaningfully improve motivation and performance? How do they align with established theories of human motivation and behaviour at work? What ethical boundaries must be respected when accessing an employee's neural data? These questions become particularly relevant in knowledge-intensive industries where performance is closely tied to mental acuity and emotional resilience.

From a theoretical perspective, motivation and productivity have been extensively studied through models such as the self-determination theory (SDT), which emphasises autonomy, competence and relatedness, and the job demands-resources (JD-R) model, which focuses on how workplace demands and resources influence employee burnout and engagement. However, the intersection of these theories with neurotechnology remains poorly defined in the current literature.

This study aims to address this gap by conducting a systematic literature review (SLR) following PRISMA 2020 guidelines, examining how neurotechnology influences cognitive processes, motivation and productivity in professional settings. Beyond mapping existing evidence, the study seeks to critically evaluate the practical benefits, theoretical alignment and ethical concerns associated with using neurotechnology in the workplace. In doing so, it contributes to both scholarly discussion and practical decision-making for HR professionals, organisational leaders and policymakers.

Purpose of the Study

The primary aim of this study is to explore how neurotechnology can influence employee motivation and productivity. With workplaces becoming more data driven, understanding the impact of neurotechnological tools can help organisations develop evidence-based HR strategies that optimise employee well-being and performance. Additionally, this study seeks to identify ethical considerations and potential challenges in implementing neurotechnology in workplace settings.

Literature Review

This study employs a literature review of peer-reviewed articles and other credible online sources. A literature review allows for the exploration of diverse perspectives from multiple studies and authors, providing a broader and more comprehensive understanding of the subject. Conducting a literature review follows a structured process that includes selecting a topic, developing an argument, searching for relevant literature, surveying and analysing the literature, critiquing findings and, finally, writing the review. Literature reviews can take various forms, including narrative reviews, integrative reviews and systematic reviews. For this study, the SLR methodology was adopted, adhering to PRISMA 2020 guidelines. A comprehensive review of peer-reviewed journals, books and conference proceedings was conducted to analyse the relationship between neurotechnology, employee motivation and workplace productivity. Relevant data were systematically extracted, evaluated and synthesised to provide a well-rounded understanding of the topic. For this systematic search, a tailored search strategy was developed using databases such as Dimensions and Google Scholar. Keywords included: *neuroscience*, *employee motivation*, *productivity*, *brain–computer interface* and *neurofeedback*. The search spanned publications from 1996 to 2025, focusing exclusively on English-language studies conducted in Asian countries. Only original research articles, review papers and conference papers were included to ensure quality and relevance. Duplicates were removed, and articles were screened for relevance through abstract analysis. A PRISMA flow diagram (Figure 1) illustrates the inclusion and exclusion process.

The reviewed studies converge on three dominant themes: the cognitive enhancement potential of neurotechnology, its role in emotional self-regulation and its influence on employee engagement and productivity. For instance, Bonetti and Casoni (2024) and Ahmed and Muhammed (2021) demonstrate how neurofeedback and BCIs support attentional control and stress reduction—factors directly linked to improved work performance. These findings suggest that neurotechnology acts as a psychological resource that supports workplace productivity. However, the literature also presents contradictory findings and limitations. While some studies praise the efficacy of neurotechnology for boosting workplace focus and emotional regulation, others caution against overreliance, technostress or ethical blind spots (Traunwieser, 2025). The variability

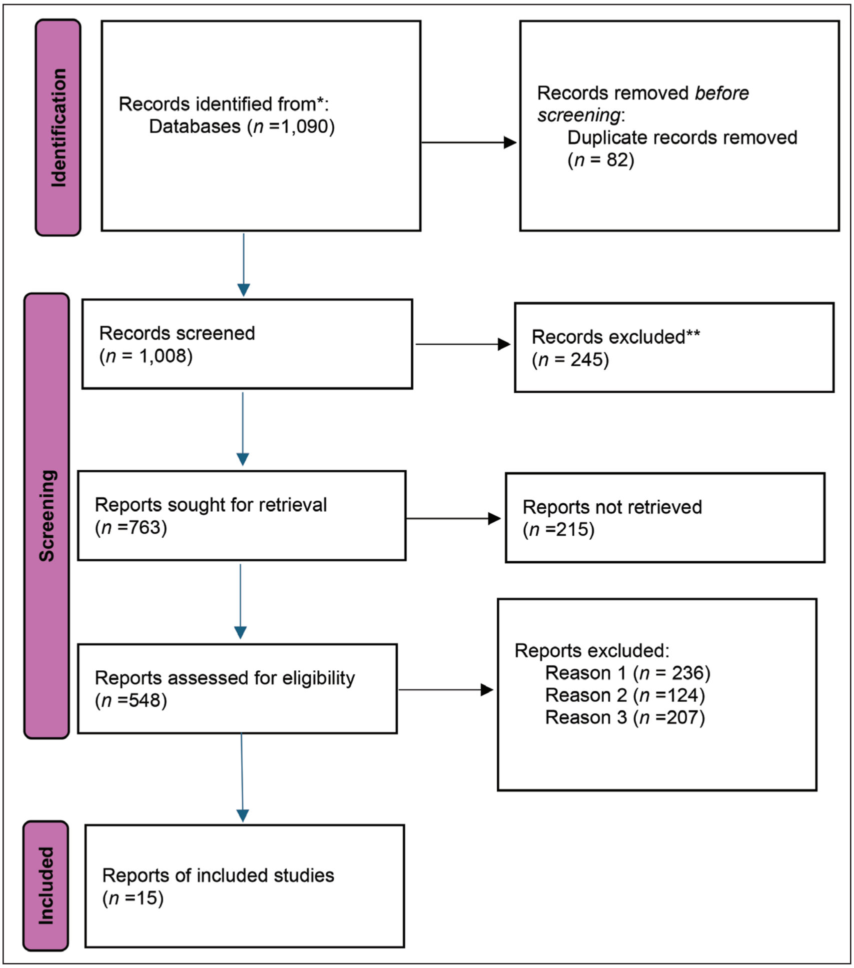

Figure 1. PRISMA Flow Diagram.

Source: The authors.

in outcomes across individual profiles and organisational contexts remains insufficiently addressed. Moreover, most existing studies lack methodological diversity, with very few longitudinal or experimental designs that could clarify causality and long-term impact.

Critically, the ethical dimension of neurotechnology in the workplace is often underdeveloped. Several scholars (e.g., Goering et al., 2017; Tindale et al., 2022) warn of serious implications regarding data privacy, autonomy and consent. Many reviewed studies fail to adequately explore the psychological effects of invasive monitoring, neuro-surveillance or pressure to conform to cognitive performance norms. These challenges signal a need for organisations to develop transparent governance frameworks before adoption. Finally, a major theoretical gap in the reviewed literature is the limited integration of foundational organisational behaviour (OB) theories. SDT, which emphasises autonomy, competence and relatedness (Deci & Ryan, 1985), offers an essential lens for evaluating how neurotechnology influences motivation. Similarly, the JD-R model (Bakker & Demerouti, 2007) could be used to assess whether neurotechnology serves as a resource or becomes an additional job demand. The reinforcement sensitivity theory (RST; Corr et al., 2016) also holds relevance, particularly when interpreting how neural feedback influences individual motivation patterns. Unfortunately, a few studies explicitly anchor their findings within these theoretical models, resulting in a disconnect between empirical findings and conceptual understanding.

The reviewed studies converge on the promise of neurotechnology but also highlight several contradictions. For instance, Ahmed and Muhammed (2021) and Bonetti and Casoni (2024) demonstrate that neurofeedback and BCIs can significantly improve attentional control and reduce workplace stress, thereby supporting employee engagement. Similarly, Miller et al. (2019) reported that EEG-based brain training interventions enhanced employees' task performance and sustained focus in high-demand environments. These findings align with the growing interest in neurotechnology as a resource for boosting productivity. However, other scholars caution against uncritical optimism. Traunwieser (2025) points to the phenomenon of technostress, where constant cognitive monitoring may overwhelm workers and erode well-being. Goering et al. (2017) and Tindale et al. (2022) further highlight ethical blind spots, particularly concerning data privacy, informed consent and neuro-surveillance in organisational contexts.

Geographically, most existing studies originate from Asian workplaces, which tend to operate in high-intensity, hierarchical contexts where such technologies are often adopted as performance enablers. This regional concentration limits generalisability, as Western or African workplaces may frame adoption differently, emphasising employee autonomy and privacy. Another limitation is methodological: many studies are cross-sectional or exploratory, with very few longitudinal or experimental designs to establish causality or long-term effects. Finally, while neurotechnology is often described as a promising workplace intervention, empirical studies rarely compare its impact against other digital tools such as wellness apps or AI-driven monitoring, leaving gaps in understanding its relative value. These contradictions and gaps underscore the need for more rigorous, diverse and cross-cultural research designs.

In summary, while the literature supports the promising role of neurotechnology in enhancing motivation and productivity, it also reveals significant methodological, ethical and theoretical gaps. Future research must bridge these deficiencies by embracing interdisciplinary frameworks, ensuring rigorous ethical practices and grounding empirical inquiry in well-established OB theories.

Objectives of the Study

1. To examine the role of neurotechnology in enhancing employee motivation and engagement

2. To analyse how neurotechnological tools, such as BCIs and neurofeedback, impact cognitive functions related to productivity
3. To identify potential ethical and privacy concerns associated with using neurotechnology in the workplace
4. To provide recommendations for organisations looking to integrate neurotechnology into their employee management strategies

Theoretical Framework

Understanding how neurotechnology influences employee behaviour requires anchoring the analysis in both neuroscientific principles and OB theories. While neuroscience explains the biological underpinnings of attention, emotion and cognition, OB theories help contextualise how these functions impact work motivation and performance. At the neuroscience level, neurofeedback and BCIs are designed to monitor and train brain activity, improving an individual's capacity for self-regulation, working memory and emotional control. These neurocognitive functions are closely linked to behaviours such as sustained attention, stress management and goal-directed thinking—all critical for workplace effectiveness. To understand how these biological enhancements influence behaviour at work, the following psychological and organisational theories are particularly relevant:

1. SDT, which posits that motivation is the highest when individuals feel autonomy, competence and relatedness. Neurotechnology may support competence by enhancing cognitive control and emotional stability, but its implementation must ensure that autonomy is not compromised through coercive or surveillance-based practices.
2. JD-R model, which asserts that workplace performance is influenced by the balance between demands (e.g., workload, stress) and resources (e.g., support, tools). Neurotechnology can be seen as a resource that boosts psychological resilience and energy levels. However, it could also introduce new demands if misused or mandated without sufficient support.

Regarding the role of neurotechnology in the workplace, it is essential to anchor the discussion in established OB theories. SDT emphasises that motivation flourishes when employees experience autonomy, competence and relatedness (Deci & Ryan, 1985). Neurotechnology may enhance competence by strengthening focus and working memory, yet it risks undermining autonomy if adoption is mandated rather than voluntary. The JD-R model (Bakker & Demerouti, 2007) further clarifies this duality: neurotechnology can function as a resource by reducing stress and improving resilience, but if poorly managed, it may create new demands in the form of technostress or surveillance pressure. RST (Corr et al., 2016) provides an additional lens, explaining how neural feedback may differentially influence individuals depending on their sensitivity to rewards or punishments.

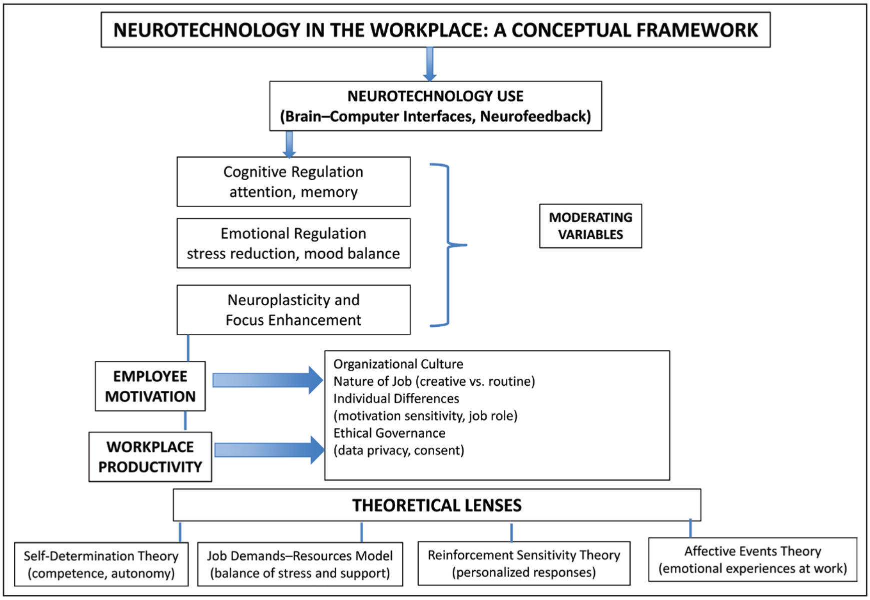

Figure 2. Neurotechnology in the Workplace: A Conceptual Framework.

Source: The authors.

Beyond these core models, theories such as psychological safety (Edmondson, 1999) and equity theory (Colquitt & Zipay, 2015) are highly relevant. If employees perceive that neural data collection threatens psychological safety, they may withdraw rather than engage. Similarly, if organisations use neurodata in ways perceived as unfair or opaque, it can erode trust and motivation. Operationalisation of these theories is critical: competence may be measured through cognitive test improvements, autonomy via surveys assessing voluntariness, job resources through reductions in reported stress and fairness through employee trust ratings. Integrating these theories ensures a more holistic understanding of how neurotechnology influences not only individual motivation but also organisational outcomes (see Figure 2).

Problem Statement

As organisations strive to enhance employee motivation and productivity in an increasingly complex and technology-driven world, attention has turned towards novel approaches that go beyond traditional HR practices. One such approach is the use of neurotechnology, including BCIs and neurofeedback systems, which aim to optimise brain functioning to improve focus, reduce stress and support cognitive performance. While the application of these tools has shown promise in clinical and therapeutic settings, their role in the workplace remains ambiguous.

Preliminary studies suggest that neurotechnology can support attention regulation, emotional control and decision-making—all of which are vital components of workplace effectiveness. However, the long-term impact, sustainability and practical application of these technologies within organisational environments are still poorly understood. In addition to functional uncertainty, several ethical dilemmas arise: How should organisations handle employees' neural data? What constitutes informed consent when using wearable neurotech devices? How can organisations ensure voluntary participation without pressuring employees to conform? These concerns become especially critical when such technologies are used in contexts where performance evaluation is tied to mental output. Moreover, there is a noticeable gap in integrating neurotechnological interventions with established motivational and OB theories, which limits the academic grounding and practical direction of existing literature. This lack of theoretical coherence weakens our understanding of how and why neurotechnology may (or may not) work in improving workforce outcomes. Therefore, this study seeks to explore and evaluate the role of neurotechnology in enhancing workplace motivation and productivity. By critically reviewing existing research through a structured SLR approach, it aims to offer insights into its practical relevance, ethical viability and theoretical alignment, while outlining the implications for future research and organisational practice.

Methodology

This study adopts an SLR methodology to synthesise the existing research on the role of neurotechnology in influencing employee motivation and workplace productivity. The review follows the PRISMA 2020 guidelines to ensure transparency, replicability and methodological rigour in the selection and evaluation of literature.

A comprehensive search was conducted using multiple electronic databases including Google Scholar and Dimensions supplemented by Scopus and Web of Science, which broadens the scope. The search was limited to peer-reviewed articles, review papers and conference proceedings published between 1996 and 2025, and only English-language studies were included. The geographical focus was restricted to Asia, given the growing interest and application of HR technology in this region.

Inclusion Criteria

The inclusion criteria were as follows: studies focused on the application of neurotechnology (e.g., BCIs, neurofeedback) in workplace or HRM contexts; empirical and conceptual papers related to motivation, productivity and cognitive performance; and articles published in credible academic journals or conferences.

Exclusion Criteria

Exclusion criteria included the following: studies related to clinical or medical applications of neurotechnology (e.g., treatment of neurological disorders), papers not published in English and duplicates and non-peer-reviewed content.

Screening Process

Out of 1,090 records identified, 82 duplicates were removed. After title and abstract screening, 763 full texts were assessed, leading to the inclusion of 15 studies that met all quality and relevance criteria. A PRISMA flow diagram was used to document the review process and ensure compliance with systematic review standards.

Data Extraction and Synthesis

Key data extracted from each selected study included: author(s), year, country, methodology, sample characteristics, neurotechnology type, key findings and theoretical lens (if any). A thematic synthesis approach was used to identify recurring patterns, contradictions and gaps in the literature. Studies were categorised by the type of neurotechnology, outcome variables (e.g., motivation, engagement, performance) and theoretical alignment.

Analysis

The distribution of publication types is illustrated in Figure 3. A trend analysis shows how research output has evolved over time (Refer to Figure 4).

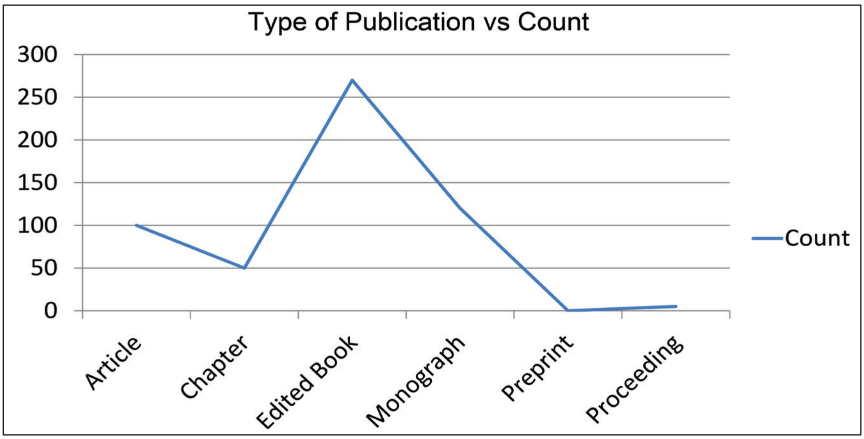

Figure 3. Publication Types.

Source: The authors.

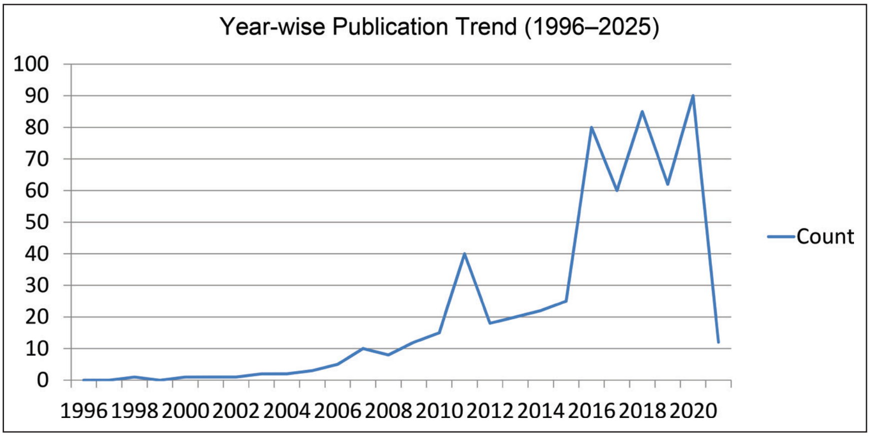

Figure 4. Year-wise Publication Trend Between 1996 and 2025.

Source: The authors.

Result and Discussion

This section presents a thematic synthesis of the 15 selected studies, focusing on three overarching dimensions: technological effectiveness, cognitive and behavioural outcomes, and ethical considerations. These themes help uncover both the promise and the complexity of neurotechnology in workplace settings.

Technological Effectiveness

The reviewed literature consistently highlights the potential of neurotechnological tools—particularly BCIs and neurofeedback devices—in enhancing employee focus, attention span and stress management (Ahmed & Muhammed, 2021; Miller et al., 2019). Such tools are increasingly being positioned as cognitive enablers that support improved performance in high-demand work environments. However, differences in the types of devices used, outcome measures and research settings pose challenges in making direct comparisons across studies.

Cognitive and Behavioural Outcomes

Neurotechnology appears to have a positive impact on emotional regulation, intrinsic motivation and task engagement. These effects align with theoretical constructs from SDT, which posits that psychological needs for competence and autonomy enhance motivation when fulfilled (Deci & Ryan, 1985). Similarly, the JD-R model offers a lens to understand how neurotechnology can function as a job resource to support well-being and performance. However, the literature also suggests that if such tools are imposed without employee consent or adequate support, they may inadvertently become sources of psychological strain or technostress.

Ethical and Practical Considerations

A critical concern across several studies involves ethical risks, especially in relation to data privacy, informed consent and employee autonomy (Tindale et al., 2022; Traunwieser, 2025). The possibility of employers using neurodata for surveillance or performance monitoring raises serious questions about workplace fairness and trust. Despite the prominence of these concerns, there is a noticeable lack of concrete ethical frameworks or implementation guidelines in the literature.

Gaps and Divergence in Research

The findings from the selected studies vary in terms of scope, methodology and contextual relevance. Most rely on exploratory or cross-sectional designs, with limited longitudinal or experimental research available. Theoretical integration also remains weak, with few studies explicitly grounding their work in established OB frameworks. Additionally, there is limited discussion on how organisational context—such as industry type or job nature—affects the applicability or outcomes of neurotechnology adoption.

In summary, while the reviewed studies demonstrate that neurotechnology has considerable potential to improve employee motivation and productivity, significant gaps remain in terms of methodological rigour, ethical clarity and theoretical alignment. These gaps must be addressed to support the responsible integration of neurotechnology in the workplace.

Conclusion

This study examined the influence of neurotechnology—specifically BCIs and neurofeedback tools—on employee motivation and workplace productivity. The findings indicate that these technologies can enhance focus, emotional stability and decision-making capabilities, which are critical for effective performance. However, these benefits are counterbalanced by ethical and organisational concerns, such as data privacy, autonomy and the risk of over-surveillance. Given these complexities, a cautious and well-informed approach is essential for integrating neurotechnology into modern HR practices.

Emerging Trends in Neurotechnology

Recent developments in workplace neurotechnology point towards significant emerging trends that are reshaping both research and practice. First, wearable EEG devices and portable BCIs are becoming increasingly affordable, moving beyond elite industries into mainstream organisational use. Companies are experimenting with headsets that measure attention and stress in real time, enabling more personalised feedback for employees. Second, AI–neurodata integration is gaining traction, where machine learning algorithms analyse brain signals to deliver individualised cognitive enhancement programs. This hybrid approach promises greater accuracy and adaptability but also raises unprecedented ethical concerns regarding data ownership and algorithmic bias.

Third, regulatory frameworks are evolving globally. The European Union's Artificial Intelligence Act has begun to address high-risk applications, including neurotechnology, while OECD guidelines stress transparency and informed consent. These developments suggest that organisations must anticipate compliance obligations as adoption expands. Fourth, the mental health and well-being agenda is increasingly linked to neurotechnology. Post-pandemic, organisations are seeking innovative solutions to manage burnout, anxiety and focus in hybrid work environments, positioning neurotech as both an opportunity for resilience and a challenge for ethical governance. Finally, future-of-work dynamics, such as hybrid and remote working models, have amplified the demand for tools that monitor engagement, cognitive load and emotional balance. While these innovations suggest a promising trajectory, they also highlight the need for balanced approaches that align technological advancement with employee rights, ethical standards and cultural sensitivities.

Managerial Implications

To move beyond theoretical interest and towards responsible implementation, managers should adopt evidence-based and context-sensitive strategies:

1. *Establish ethical governance frameworks:* Create organisational policies that cover consent, data protection, usage boundaries and transparency. Reference best practices from bioethics and digital governance (Goering et al., 2017).
2. *Develop training and awareness protocols:* Train both managers and employees in the purpose, limitations and ethical considerations of neurotechnology to reduce fear, misunderstanding and misuse.
3. *Customise implementation by industry type:*
    - In knowledge-intensive sectors, where focus and emotional regulation are critical, technologies like neurofeedback may offer substantial ROI.
    - In labour-intensive or routine-task environments, simpler tools (e.g., fatigue-monitoring wearables) might be more appropriate.
4. *Pilot programmes with voluntary participation:* Roll out small-scale trials where employees opt in voluntarily. Evaluate impact using both quantitative metrics (e.g., productivity, attention scores) and qualitative feedback (e.g., user comfort, perceived benefit).
5. *Encourage cross-disciplinary collaboration:* Involve HR, legal, IT and occupational health experts to ensure well-rounded and compliant neurotech strategies.

These recommendations aim to help organisations ethically and effectively leverage the promise of neurotechnology while minimising potential harms.

Limitations of the Study

This study is limited by its reliance on secondary data and the scope of its literature review. The geographic focus on Asian contexts may limit the generalisability of findings to other regions. Furthermore, clinical applications of neurotechnology and its potential uses in creative or artistic job roles were excluded from the review. The study also does not address the differential effects of neurotechnology on individual versus team-level outcomes, nor does it assess variations across demographic groups.

Scope of Future Research

To advance the understanding and practical applications of neurotechnology in organisational contexts, future research should focus on the following areas:

1. *Experimental and longitudinal studies:* There is a need for well-designed experiments that assess the causal effects of neurofeedback or BCIs on workplace behaviour and motivation over time.
2. *Multi-level and sector-specific analysis:* Research should examine how neurotechnology affects employees at individual, team and organisational levels and how these outcomes differ across industries such as healthcare, manufacturing, education and IT.
3. *Integration with OB theories:* Future studies should embed neurotechnology research within established OB frameworks such as SDT, JD-R or RST, to better explain motivational outcomes and guide practice.
4. *Ethical and regulatory exploration:* More research is needed to develop ethical models and policy guidelines that can inform safe and inclusive implementation. Particular attention should be given to the challenges of informed consent, equity and surveillance.

By addressing these gaps, future research can contribute to a more nuanced and responsible understanding of how neurotechnology can shape the future of work.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship and/or publication of this article.

Funding

The authors received no financial support for the research, authorship and/or publication of this article.

ORCID iDs

Triptii Shelkke https://orcid.org/0009-0006-0574-9792
Divya Rahul Jain https://orcid.org/0000-0002-1595-489X

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Empirical Research

Determinants of Foreign Exchange Reserves in India

GLIMS Journal of Management Review and Transformation
4(2) 138–160, 2025

DOI: 10.1177/jmrt.251389387
mrt.greatlakes.edu.in

Arjumand Qadir[1] and Mohammed Ayub Soudager[2]

Abstract

This study investigates the determinants of foreign exchange reserves in India using quarterly data from 2000Q1 to 2020Q4. Employing a structured two-stage framework, the analysis first derives a long-run money demand function through the ARDL bound testing approach, from which a domestic money market disequilibrium term is generated. This term is then integrated into the short-run reserve demand function using an unrestricted error-correction model. The empirical findings reveal that the average propensity to import exerts a strong negative long-run effect on reserves (elasticity: –1.21), while foreign portfolio investment (elasticity: 0.51) and short-term external debt (elasticity: 0.55) have significant positive effects. In the short run, money market disequilibrium negatively influences reserves (coefficient: –1.02), with an error-correction adjustment speed of 11% per quarter. Reserve adequacy diagnostics further confirm that by 2020, India's reserves covered 12 months of imports, exceeded short-term external debt by a factor of more than two and represented over 20% of broad money supply, far surpassing international adequacy thresholds. These results demonstrate that India's reserve accumulation, though precautionary in nature, has generated a consistent surplus beyond conventional benchmarks. The study concludes that such surplus reserves can be strategically redeployed towards external debt reduction and high-return domestic investments, thereby optimising the balance between precautionary holdings and development financing. In doing so, the findings highlight important societal benefits, including enhanced macroeconomic stability, reduced fiscal costs and the creation of fiscal

[1] Department of Economics, University of Kashmir, Srinagar, Jammu and Kashmir, India
[2] Centre for Distance and Online Education, University of Kashmir, Srinagar, Jammu and Kashmir, India

Corresponding author:
Arjumand Qadir, Department of Economics, University of Kashmir, Srinagar, Jammu and Kashmir 190006, India.
E-mail: arjumand.ecscholar@kashmiruniversity.net

space for health, education and infrastructure, consistent with the objectives of sustainable growth. By integrating updated evidence with actionable policy recommendations, this article contributes to the discourse on dynamic reserve management in emerging economies.

Keywords

Economic and business policy, financial economics, international management, policy

Submitted 24 August 2025; received 16 September 2025; accepted: 25 September 2025

Introduction

Foreign exchange reserves constitute a cornerstone of macroeconomic stability and resilience for emerging economies such as India. According to the International Monetary Fund (IMF, 2013), foreign exchange reserves include foreign currency assets, gold, special drawing rights and a nation's reserve position with the IMF—assets that are readily available to the monetary authority for external obligations and market interventions. Beyond their immediate financial role, reserve management also connects to broader sustainability objectives. In particular, the strategic redeployment of surplus reserves can contribute to the Sustainable Development Goals (SDGs), especially SDG 8 (promoting sustained, inclusive and sustainable economic growth), SDG 9 (building resilient infrastructure and fostering innovation) and SDG 17 (strengthening global financial partnerships and stability). This study addresses the problem of excess reserve accumulation, which, while enhancing stability, imposes fiscal and opportunity costs. By analysing the determinants of reserves and evaluating adequacy benchmarks, this article presents solutions that allow for optimising the balance between precautionary holdings and growth-oriented investments. This represents the unique contribution of the study: integrating advanced econometric evidence with sustainability-linked policy recommendations.

Historically, under the Bretton Woods system of fixed exchange rates, reserves played a pivotal role in maintaining currency pegs. Although the system collapsed in the early 1970s and most economies transitioned to more flexible or managed float regimes, global reserve holdings have continued to grow substantially. India exemplifies this paradoxical trend. Following the adoption of a market-determined exchange rate system in March 1993, India's foreign exchange reserves had surged from approximately US$9.8b to over US$550b by February 2022, positioning the country among the top reserve holders globally. This rapid accumulation reflects multiple objectives, including safeguarding against external shocks, maintaining orderly exchange rate conditions and supporting policy credibility.

Theoretical frameworks suggest that under a freely floating exchange rate system, reserves should be minimal, as currency values adjust automatically through market forces. Conversely, fixed or managed exchange rate regimes necessitate higher reserves to manage currency stability. Despite India's managed float regime, its reserves have persistently exceeded traditional adequacy thresholds, prompting debate over the factors driving this accumulation and the optimal level of reserves.

Existing studies have examined the determinants of India's foreign exchange reserves, often incorporating macroeconomic variables such as trade openness, capital flows and opportunity costs. Some have explored the role of domestic money market disequilibrium in explaining reserve fluctuations (Mishra & Sharma, 2011; Nayak & Baig, 2019). However, much of this literature relies on outdated data sets and does not capture the significant macroeconomic transformations India has undergone in the past decade, including heightened capital mobility, policy reforms and unprecedented reserve growth post the global financial crisis and during the COVID-19 period. To address this limitation, the present study employs an updated quarterly data set covering the period from 2000Q1 to 2020Q4, enabling a re-examination of reserve dynamics in light of recent economic developments. Methodologically, the present study adopts a structured two-stage approach: first, a domestic money market disequilibrium variable is derived from an estimated long-run money demand function; second, this measure is integrated into both long-run and short-run reserve demand models using the ARDL bound testing and unrestricted error-correction model (UECM) frameworks. Furthermore, the study evaluates India's reserve adequacy against established international benchmarks, providing quantitative evidence of surplus holdings.

The objective of the study is to examine both the long-run and short-run determinants of reserves, explicitly incorporating domestic money market disequilibrium into an ARDL–UECM framework. The novelty lies in three contributions: first, the use of quarterly data spanning 2000–2020, which allows for the inclusion of the post–global financial crisis, recent policy reforms and the COVID-19 period; second, the explicit modelling of monetary disequilibrium within a unified econometric structure to assess both equilibrium and adjustment dynamics; and third, the integration of econometric findings with reserve adequacy diagnostics to provide actionable policy recommendations on optimal reserve deployment. Collectively, these contributions advance the literature by offering updated empirical evidence and by linking reserve dynamics to practical strategies for economic management in emerging markets.

Adequacy of Foreign Exchange Reserves in India

Over the past three decades (1991–2020), India's foreign exchange reserves have expanded substantially, reflecting a deliberate strategy to strengthen external sector resilience and safeguard against global financial volatility. The literature identifies several well-established benchmarks to assess whether a country's reserve holdings are adequate relative to its potential external vulnerabilities. This section evaluates India's reserves against three commonly accepted adequacy indicators: the import cover ratio, the ratio of reserves to short-term external debt and the ratio of reserves to broad money supply.

Reserves in Terms of Months of Imports

A widely used rule-of-thumb for reserve adequacy is the number of months of imports that reserves can cover. This measure accounts for a country's dependence on external trade and its susceptibility to external shocks. Although there is no universal benchmark, economists generally consider reserves equivalent to at least 3–6 months of imports to be sufficient for meeting short-term external obligations and maintaining market confidence (Mishra & Sharma, 2011). As shown in Figure 1, India's import cover has consistently exceeded this minimum standard since 2000. By 2020, country's reserves were sufficient to cover approximately 12 months of imports, providing a substantial buffer against trade and capital flow shocks.

Ratio of Reserves to Short-term External Debt

For countries with significant exposure to international borrowing, the ratio of reserves to short-term external debt serves as a critical indicator of liquidity risk. Short-term debt is particularly vulnerable to sudden stops or reversals in capital flows, making this ratio a key gauge of a country's ability to withstand external financing pressures (Bird & Rajan, 2003). According to the Greenspan–Guidotti rule, a country should maintain reserves at least equal to its short-term external debt to safeguard against rollover risks (Jeanne, 2007; Mishra & Sharma, 2011). Figure 2 illustrates that since 2000, India's reserves have consistently remained above this threshold. Although the ratio has declined since its peak in 2004, it has consistently stayed above 1, indicating a sound liquidity position and sustaining investor confidence.

Ratio of Reserves to Broad Money (M3)

Another useful measure of reserve adequacy is the ratio of reserves to broad money supply (*M3*). This ratio reflects the degree of exposure to rapid capital

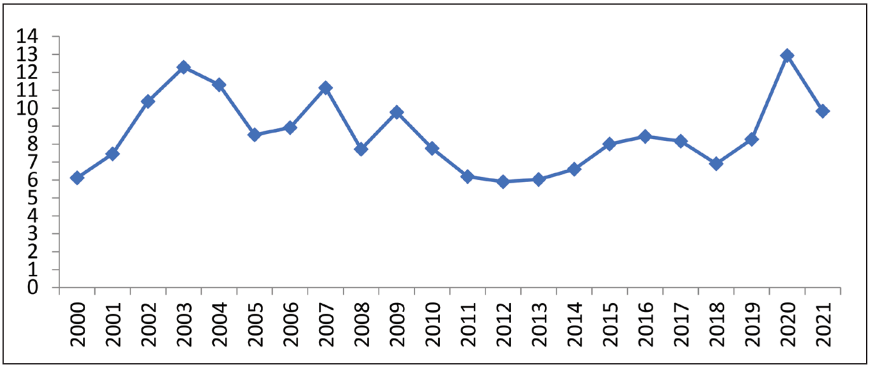

Figure 1. Foreign Exchange Reserves in Terms of Months of Imports.

Source: World Development Indicators, World Bank.

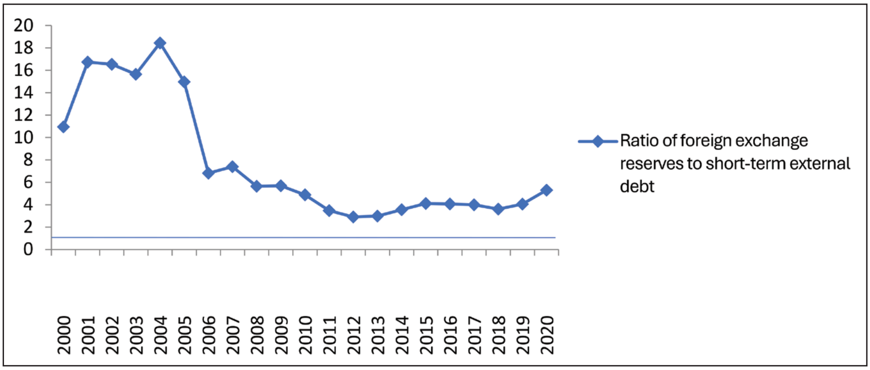

Figure 2. Ratio of Foreign Exchange Reserves to Short-term External Debt.

Source: World Development Indicators, World Bank.

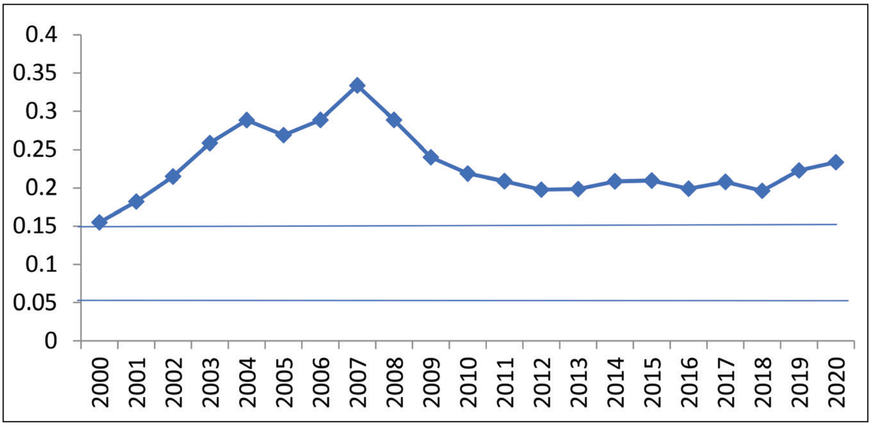

Figure 3. Ratio of Foreign Exchange Reserves to Broad Money.

Source: Reserve Bank of India.

flight, as broad money represents the domestic liquidity that could potentially be converted into foreign assets during periods of financial stress. Calvo and Mendoza (1996) suggest that a ratio in the range of 5%–15% is typically considered adequate to mitigate currency and banking crises. Figure 3 demonstrates that India's reserves have remained well above this benchmark range since 2000, underscoring the strength of its external position relative to the size of its domestic monetary base.

Together, these standard metrics confirm that India's foreign exchange reserves not only meet but significantly exceed traditional adequacy norms, highlighting a consistent policy preference for maintaining a robust buffer against external shocks. This surplus suggests an opportunity for policymakers to explore more efficient allocations of excess reserves to support domestic development priorities and reduce the economic cost of holding large reserve stocks.

Literature Review

The accumulation of foreign exchange reserves has attracted wide academic attention, and the literature can broadly be grouped into four themes: precautionary motives, mercantilist motives, institutional and structural determinants, and country-specific evidence. This thematic classification enables a critical synthesis of existing research while identifying the specific gaps addressed by the present study.

Precautionary Motives

A large strand of literature views reserves primarily as a buffer stock against external shocks, sudden stops in capital flows or balance-of-payments crises. Aizenman and Lee (2007) demonstrated that reserves rise significantly in response to crisis indicators, trade openness and financial volatility, confirming the importance of precautionary motives in emerging markets. Cheung et al. (2019) extended this argument to the regional context, showing that countries often accumulate reserves in response to the behaviour of their peers—a phenomenon they called the 'Joneses effect'. In the Indian context, Prabheesh et al. (2007) used an ARDL framework and found that both precautionary and mercantilist motives were statistically significant, but the precautionary motive was particularly relevant due to the volatility of portfolio flows. Similarly, Mishra and Sharma (2011) showed that monetary disequilibrium, in combination with precautionary factors, explained India's reserve accumulation under the floating regime. These studies highlight the dominant role of precautionary accumulation but leave open questions about how disequilibrium interacts with external determinants over longer time horizons.

Mercantilist Motives

Another influential strand interprets reserve accumulation as a deliberate strategy to support export competitiveness and resist exchange rate appreciation. Ford and Haung (1994) demonstrated for China that reserve demand was closely tied to trade performance and the average propensity to import (API). Aizenman and Lee (2007) found that deviations from purchasing power parity and export growth reinforced mercantilist accumulation.

For India, Prabheesh et al. (2007) found robust evidence of mercantilist motives during the early liberalisation phase, suggesting that policymakers used reserves to maintain competitiveness in global markets. Pontines and Rajan (2011) further showed that many Asian central banks intervened in foreign exchange markets to prevent appreciation, thereby contributing to persistent reserve build-up. Collectively, these studies underscore the mercantilist interpretation of reserves as a policy tool for trade and currency management. However, the relative strength of this motive in more recent years remains contested, particularly in the context of large-scale capital inflows.

Institutional and Structural Determinants

A growing body of research highlights the role of institutional quality, financial liberalisation and structural reforms in shaping reserve demand. Law et al. (2021) provided cross-country evidence that institutional quality exhibits a nonlinear relationship with reserves: accumulation initially rises with improvements in institutions but declines beyond a certain threshold. Aizenman and Marion (2003) and Ramachandran (2004) emphasised that adjustment costs, policy credibility and risk perceptions act as structural determinants of reserve demand, beyond trade and financial variables.

For South Asia, Nayak and Baig (2019) provided important evidence on the role of money market disequilibrium, showing that imbalances in domestic liquidity significantly influenced reserve holdings in both India and China. Dominguez et al. (2012) argued that emerging-market central banks prioritise stability over opportunity costs when deciding on reserve levels, underscoring the institutional and credibility dimensions of accumulation. This line of work highlights that reserve dynamics cannot be understood purely in terms of macroeconomic flows but must also account for institutional frameworks and policy choices.

Country-specific Evidence

Country-focused studies provide further nuance by highlighting context-specific determinants. For China, Ford and Haung (1994) documented the role of monetary disequilibrium and imports in shaping reserves. For Bangladesh, Chowdhury et al. (2014) found strong relationships between reserves, remittances, the exchange rate and domestic interest rates, while foreign aid was insignificant. In Sri Lanka, Kashif and Sridharan (2020) reported that trade deficits and external debt pressures constrained reserve accumulation. For India, Mishra and Sharma (2011) found that monetary disequilibrium played a central role, while Nayak and Baig (2019) highlighted the joint role of disequilibrium and external flows in explaining reserve dynamics. These country-level studies reinforce the view that determinants vary with institutional setting, external exposure and domestic macroeconomic structures.

Synthesis and Gaps

Taken together, the literature provides valuable insights but also leaves important gaps. While precautionary and mercantilist motives are well established, their relative strength in the Indian context during the past two decades of capital liberalisation remains underexplored. Similarly, although monetary disequilibrium has been included in some models, it has rarely been systematically integrated into both long- and short-run frameworks. Moreover, much of the existing evidence relies on outdated data sets, often ending before the global financial crisis or excluding the COVID-19 period, thereby missing major structural changes in India's external sector.

The present study addresses these limitations by employing quarterly data up to 2020, explicitly deriving a money market disequilibrium variable and examining its role alongside traditional determinants in both the ARDL long-run framework and the UECM short-run model. Further, by incorporating reserve adequacy diagnostics, the study links econometric evidence to sustainability-oriented policy recommendations, thereby advancing the discourse on dynamic reserve management in emerging economies.

Data Sources

This study utilises quarterly data spanning the period from the first quarter of 2000 (2000Q1) to the fourth quarter of 2020 (2020Q4). Data on foreign exchange reserves (*ir*), broad money (*m3*), imports, gross domestic product (GDP), domestic interest rate (*r*) and exchange rate (*er*) were obtained from the Federal Reserve Bank of St. Louis (FRED) database. In addition, data on foreign portfolio investment (*fpi*) and short-term external debt (STED) were sourced from the Reserve Bank of India's *Handbook of Statistics on the Indian Economy*.

Prior to conducting the econometric analysis, all variables—except for the opportunity cost—were transformed into their natural logarithmic form.

Methodology

The empirical analysis is conducted in three stages to systematically capture the long-run and short-run determinants of India's foreign exchange reserves and to account explicitly for the role of domestic money market disequilibrium. For clarity, Figure 4 provides a graphical summary of the three-stage empirical methodology adopted in this study.

In Stage 1, a long-run money demand function is estimated using the ARDL framework to derive a domestic money market disequilibrium variable (M^{Dis}). In Stage 2, a long-run reserve demand function is estimated using ARDL bound testing. In Stage 3, the short-run reserve demand function is modelled within a UECM framework, explicitly incorporating the disequilibrium term.

Long-run Money Demand Function and National Money Market Disequilibrium (Stage 1)

According to the classical quantity theory of money, the demand for nominal money balances is primarily determined by three variables: income, the general price level and the interest rate. Specifically, the demand for nominal money balances is assumed to be a positive function of income and the price level, and a negative function of the interest rate. In empirical applications, it is common practice to model the demand for real money balances as positively related to real income and inversely related to the interest rate. Consistent with this theoretical framework and empirical literature, the long-run money demand function in this study is specified using the ARDL approach proposed by Edwards (1984).

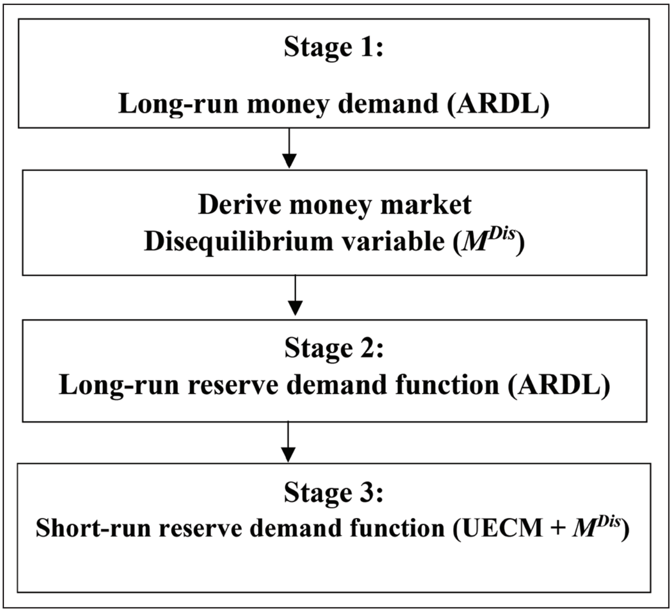

Figure 4. Graphical Summary of the Three-stage Empirical Methodology Adopted in This Study.

$$lnM_t = \alpha_0 + \alpha_1 \sum\nolimits_{i=1}^{p} lnM_{t-i} + \alpha_2 \sum\nolimits_{i=0}^{q} lnGDP_{t-i} + \alpha_3 \sum\nolimits_{i=0}^{r} r_{t-i} + \alpha_4 \sum\nolimits_{i=0}^{s} lnER_{t-i} + \mu_t \quad (1)$$

where M_t is broad money stock ($M3$), GDP_t is real output, r_t is domestic short-term interest rate, ER_t is nominal exchange rate (INR/USD) and u_t is error term. The fitted value represents equilibrium money demand, M^*_t.

From this model, the money market disequilibrium term is derived as the deviation of actual money supply from its estimated demand. The specification is as follows:

$$MDis_t = M_{t-1} - M^*_t \quad (2)$$

where $MDis_t$ represents the money market disequilibrium in period t.

We retain the level form consistent with ARDL residuals. A log-deviation version yields similar results.

In line with the standard monetary and international finance literature, the expected signs of the model variables can be explained as follows. The coefficient on income (GDP_t) is expected to be positive, since rising income increases transaction demand for money as individuals and businesses engage in more consumption and investment. Conversely, the interest rate (r_t) is anticipated to have a negative sign, reflecting the higher opportunity cost of holding money when returns on alternative assets rise. The exchange rate (ER_t) carries an ambiguous sign: depreciation may increase domestic money demand through a wealth effect (rising value of foreign assets) but can also lower demand through currency substitution if agents switch into foreign currency holdings.

The long-run money demand function is estimated using the ARDL bound testing approach, which allows for a mix of stationary and non-stationary regressors and provides robust estimates of both long-run relationships and short-run dynamics. The results of the unit root tests indicate that all variables are integrated of order one, $I(1)$, and are given in Table A1. The existence of a long-run relationship among the variables is confirmed by the computed F-statistic from the bound test (Table 1).

The value of F-statistic is 19.33, which lies above the upper critical bound. It means there exists a long-run relationship between money demand and its determinants. The long-run results of ARDL model are reported in Table 2.

The estimated long-run money demand function confirms that all variables are stationary and exhibit signs consistent with theoretical expectations. Specifically, the coefficient of the ER is negative, indicating that a depreciation of the domestic currency tends to increase expectations of further depreciation, prompting economic agents to substitute domestic currency holdings with foreign currencies. This finding aligns with the results reported by Bahmani-Oskooee and Poorheydarian (1990), who have also documented evidence supporting the currency substitution effect in open economies.

Table 1. Bound Test for Existence of Long-run Relationship Among Variables Included in Money Demand Function.

		Critical Bound	
F-statistics	Significance Level (%)	$I(0)$	$I(1)$
19.33	10	2.01	3.1
	5	2.45	3.63
	1	3.42	4.84

Table 2. ARDL Results of Long-run Money Demand Function.

Dependent Variable: *lnm3*				
Variables	Coefficient	Std. Error	*t*-statistic	Prob.
Lngdp	1.063585	0.013075	81.34556	.0000
LnER	−0.882821	0.224412	−3.933930	.0000
R	−0.056404	0.028245	−1.997965	.0497
Diagnostic Statistics				
R^2 = 0.998481				
SE of regression = 0.016				
F-statistic = 5,229.913		Prob. (*F*-statistic) = .0000		
CUSUM = Stable		CUSUMSQ = Stable		
ARCH = 0.17 (0.67)		LM = 2.01 (0.14)		

Long-run Reserve Demand Function (ARDL) (Stage 2)

In the second stage, the long-run reserve demand function is estimated. Consistent with the theoretical framework, the money market disequilibrium term is excluded from the long-run model, as it is assumed to have only short-run transitory effects. The long-run reserve demand function (ARDL model) specified in this study is as follows:

$$lnR_t = \beta_0 + \beta_1 \sum_{i=1}^{p} lnR_{t-i} + \beta_2 \sum_{i=0}^{q} ln\mathrm{API}_{t-i} + \beta_3 \sum_{i=0}^{r} lnFPI_{t-i} + \beta_4 \sum_{i=0}^{s} lnSTED_{t-i} + \beta_5 \sum_{i=0}^{t} lnER_{t-i} + \beta_6 \sum_{i=0}^{u} OC_{t-i} + \mu_t \quad (3)$$

where lnR is log of reserves/GDP, $lnAPI_t$ is log of imports/GDP, $lnFPI_t$ is log of portfolio inflows/GDP, $lnSTED_t$ is log of short-term external debt/GDP, $lnER_t$ is log of exchange rate, OC_t is opportunity cost (interest rate differential, % points) and ε_t is error term.

In the literature, countries accumulate foreign exchange reserves for multiple reasons, commonly categorised as transaction, precautionary and mercantilist motives. To capture the transaction motive, the API is included in the model. The expected sign of API can be either positive or negative, depending on its impact on the trade balance. If an increase in API is associated with a trade surplus—where export growth outpaces import growth, it can contribute to higher reserve accumulation. Conversely, if rising API leads to a trade deficit, it can exert downward pressure on reserves. Thus, the net effect of API on reserve holdings is conditional on the country's trade balance dynamics.

To capture the precautionary motive, foreign portfolio investment (FPI) and STED are incorporated as explanatory variables. Portfolio inflows are typically volatile, and countries often accumulate reserves as a safeguard against sudden capital flight; hence, the expected sign for FPI is positive. Similarly, STED represents a potential source of external vulnerability: higher short-term debt obligations increase the need for reserves to mitigate rollover risk and liquidity crises, implying a positive expected sign for this variable as well.

The exchange rate (ER) variable is included to account for currency substitution and valuation effects, while the opportunity cost (OC) reflects the foregone return from holding reserves relative to alternative assets. The effect of the ER on reserves is again theoretically ambiguous: depreciation may trigger precautionary accumulation but can also induce capital flight. Finally, the OC of holding reserves is expected to be negative, since higher interest differentials make reserve accumulation costlier relative to domestic investment opportunities.

Remittances, while important for India's external balance, are relatively stable and countercyclical compared to portfolio flows and short-term debt. Several studies (e.g., Chami et al., 2008; IMF, 2016) show that remittances primarily support household consumption and are less volatile, reducing their direct role in shaping precautionary reserve demand. Similarly, global oil price shocks are an important determinant of the trade balance; however, their effect is already captured indirectly through the imports-to-GDP ratio (API), which includes

India's substantial oil import bill. Including both oil prices and API would risk multicollinearity and redundancy. For these reasons, remittances and oil price shocks were excluded to maintain a parsimonious specification while focusing on the core determinants most directly related to precautionary and financial stability motives.

The long-run relationship between reserve demand and its determinants is assessed using the ARDL bound testing approach. The computed *F*-statistic is reported in Table 3.

The value of *F*-statistic is 12.89, which lies above the upper critical bound. There exists long-run relationship between reserves and their determinants. Then, the long-run reserve demand model has been estimated by ARDL, and the results are reported in Table 4.

The empirical results indicate that all explanatory variables, except for the OC, are statistically significant and exhibit the expected signs. This suggests that the Reserve Bank of India's decision to hold foreign exchange reserves is motivated primarily by the need to safeguard macroeconomic stability and provide a buffer against external shocks, rather than by considerations of potential alternative returns from investing these reserves abroad.

The coefficient of API (*lnapi*) is −1.209, which is statistically significant at the 1% level (p = .0003). This negative relationship implies that an increase in the

Table 3. Bound Test for Existence of Long-run Relationship Among Variables Included in Reserve Demand Function.

F-statistics	Significance Level (%)	Critical Bound *I*(0)	Critical Bound *I*(1)
19.33	10	1.81	2.93
	5	2.14	3.34
	1	2.82	4.21

Table 4. ARDL Results of Long-run Reserve Demand Function.

Dependent Variable: *lnr*				
Variables	Coefficient	Std. Error	*t*-statistic	Prob.
lnapi	−1.209457	0.319951	−3.780134	0.0003
Lnfpi	0.511279	0.156843	3.259813	0.0018
lnsted	0.553755	0.129224	4.285219	0.0001
Oc	−0.014451	0.023395	−0.617684	0.5389
lner	1.687767	0.291782	5.784335	0.0000
Diagnostic Statistics				
R^2 = 0.996920	Adjusted R^2 = 0.996257			
SE of regression = 0.047959				
F-statistic = 1,502.793	Prob. (*F*-statistic) = 0.0000			
ARCH = 0.90 (0.34)	LM = 1.64 (0.20)			
CUSUM test = Stable				

API is associated with a decline in foreign exchange reserves in the long run. The negative and significant coefficient of API is in line with the findings of Chakrabarty and Bordoloi (2013), who argue that higher imports increase the current account deficit, thereby reducing the capacity for reserve accumulation. The coefficient of foreign portfolio investment (*lnfpi*) is positive, implying that higher portfolio inflows are associated with higher reserves. This is due to precautionary motive of accumulating reserves as insurance against volatile capital flows. These results are in line with the findings of Aizenman and Lee (2007) and Mohanty and Turner (2006).

The insignificance of OC variable aligns with the findings of Dominguez et al. (2012), who emphasise that in emerging markets, central banks prioritise macroeconomic stability over OC considerations.

Diagnostic tests confirm that the residuals are free from both autocorrelation and heteroscedasticity. This indicates that the estimated model adequately captures the underlying dynamics of the data and that the residuals do not display any systematic patterns or variance instability that would undermine the reliability of the results.

Short-run Reserve Demand Function (UECM +M^{Dis}) (Stage 3)

Finally, the short-run reserve demand function is estimated by incorporating the money market disequilibrium term along with the short-run dynamics of the other determinants. The short-run UECM is a statistical model that combines the short-run dynamics of the variables with their long-run equilibrium relationship. The ordinary least squares (OLS) approach has been used for estimating the parameters of the short-run UECM and follows the specification:

$$\Delta lnR_t = \delta_0 + \Sigma\delta_{1i}\,\Delta lnR_{t-i} + \Sigma\gamma_j\,\Delta lnX_{j,t-1} + \varphi MDis_{t-1} + \psi ECT_{t-1} + \eta_t \quad (4)$$

where Δ is the first difference operator, $X_{j,t}$ is the vector of logged regressors (*lnAPI*, *lnFPI*, *lnSTED*, *lnER*););,; OC_t is included as appropriate, $MDis_{t-1}$ is the lagged disequilibrium, ECT_{t-1} is the lagged error-correction term from Equation (3) and η_t is the error term.

ψ measures the speed of adjustment; that is, ψ measures the speed at which deviations from equilibrium are corrected. In other words, it measures the extent to which changes in the foreign exchange reserves are influenced by its past deviations from its long-run equilibrium relationship with one or more independent variables.

The money market disequilibrium measure ($MDis_t$) is expected to exert a negative effect on reserves, as excess liquidity in the domestic money market tends to pressure the balance of payments and lower reserve holdings, whereas the error-correction term (ECT_t) is anticipated to be negative, capturing the speed of adjustment back to long-run equilibrium.

The short-run results estimated from OLS approach are shown in Table 5.

The short-run results indicate that all explanatory variables are statistically significant, highlighting their relevance in explaining fluctuations in foreign

Table 5. Short-run Reserve Demand Model with Monetary Disequilibrium.

Dependent Variable: Δlnr_gdp				
Variables	Coefficient	Std. Error	*t*-statistic	Prob.
Δlnr_{t-2}	0.237	0.015	1.83	.0718
$\Delta lnapi_{t-2}$	0.244	0.119	2.04	.0452
Δoc_{t-1}	−0.007	0.003	−2.09	.0410
$\Delta lnfpi_{t-1}$	0.059	0.011	5.05	.0000
$\Delta lnsted_{t-1}$	−0.127	0.053	−2.37	.0212
$\Delta lner_{t-2}$	0.639	0.277	−2.30	.0248
ECT_{t-1}	−0.111	0.055	−2.01	.0488
$MDis_{t-1}$	−1.02	0.302	−3.61	.0006
Diagnostic Statistics				
R^2 = 0.480217				
SE of regression = 0.04				
F-statistic = 5.17		Prob. (*F*-statistic) = .000		
LM = 0.57(0.56)		ARCH = 0.01(0.89)		

exchange reserves over shorter time horizons. The coefficient of the error-correction term (ECT) is –0.11, suggesting that approximately 11% of the previous period's disequilibrium is corrected in each quarter. This moderate speed of adjustment implies that deviations from the long-run equilibrium are gradually realigned over time through adjustments in reserve holdings.

The coefficient of the money market disequilibrium variable is negative and statistically significant. This indicates that imbalances in the money market—where the supply of money exceeds or falls short of demand—have a direct effect on foreign exchange reserves in the short run. In cases of excess money supply, declining interest rates may render the domestic currency less attractive to foreign investors, thereby reducing capital inflows and exerting downward pressure on foreign exchange reserves. This finding supports the theoretical expectation that money market imbalances can influence currency markets and reserve behaviour through interest rate channels.

One unexpected finding in the short-run model is the negative and statistically significant coefficient of STED. While theory suggests that higher short-term liabilities should increase the demand for reserves as a precautionary buffer, the short-run dynamics in India appear to operate differently. A plausible explanation is that sudden increases in short-term debt obligations may undermine investor confidence in the economy's external sustainability. In such cases, rather than prompting precautionary reserve accumulation, rising STED may trigger capital outflows, currency depreciation pressures and downward movements in reserves. This interpretation is consistent with the literature on 'sudden stops' and external vulnerability (Calvo, 1998; Rodrik & Velasco, 1999), which emphasises that markets may perceive sharp increases in short-term debt as a signal of fragility, thereby worsening reserve positions in the short term.

In India's case, the negative short-run effect of STED likely reflects these risk perceptions. However, the positive and significant long-run relationship between STED and reserves remains intact, supporting the view that policymakers eventually respond to higher debt obligations by building up reserves as an insurance mechanism. This combination of short-run vulnerability and long-run precautionary adjustment highlights the dual role of reserves in emerging markets: while markets may react negatively to sudden debt surges in the short run, central banks act over time to restore confidence by strengthening reserve buffers.

Diagnostic Tests

To ensure the reliability of the estimated models, a series of diagnostic tests were conducted. Standard residual diagnostics confirmed the absence of autocorrelation and heteroscedasticity, while the Jarque–Bera test supported normality of residuals.

In addition, parameter stability was examined using the CUSUM and CUSUM of squares (CUSUMQ) tests. For both the long-run money demand function and the reserve demand function, the test statistics remained within the 5% significance bounds, thereby confirming the stability of the estimated coefficients and the absence of structural instability over the sample period. The graphical plots of these stability diagnostics are presented in Figures B1–B4.

Together, these results validate that the estimated ARDL specifications are econometrically sound and robust, providing a solid basis for interpreting both the long-run and short-run relationships identified in this study.

The evaluation of the determinants of foreign exchange reserves carries important societal implications. By identifying the role of monetary disequilibrium, trade performance and capital flows, this study contributes to policies that enhance macroeconomic stability, which in turn protects employment, ensures affordable imports of essential goods and shields the economy from disruptive crises. Furthermore, the findings on reserve adequacy inform decisions on the optimal use of surplus reserves. Reallocating excess reserves towards external debt reduction and productive domestic investment can lower fiscal burdens, free resources for priority social sectors such as health and education, and stimulate infrastructure development. In this way, the research not only advances the academic literature but also generates actionable insights that align with societal welfare and long-term sustainable development.

To situate the results in a broader context, this sub-section highlights the research problems addressed, the solutions offered by the findings and the theoretical contributions of the study.

In India's case, three challenges motivated the research: (a) much of the existing literature relies on pre-crisis data sets and ignores recent structural shifts, (b) the interaction between precautionary and mercantilist motives and domestic monetary disequilibrium remains underexplored and (c) adequacy benchmarks are often cited without linking them to econometric evidence or policy trade-offs.

The results provide clear solutions. Imports have a strong negative long-run effect on reserves (elasticity –1.21), showing that trade shocks remain a key vulnerability—thereby updating the evidence base with recent data. Portfolio inflows emerge as a significant positive determinant, confirming their role as both a driver of reserve accumulation and a source of volatility. Most importantly, incorporating money market disequilibrium reveals that reserves are also shaped by internal liquidity imbalances, not only external shocks. This bridges monetary theory with reserve demand and offers a more integrated framework.

Adequacy diagnostics confirm that India's reserves consistently exceed precautionary thresholds. This implies that a portion of surplus reserves could be redeployed towards external debt repayment or productive domestic investment, reducing fiscal burdens and supporting growth.

The theoretical contribution lies in synthesising competing perspectives. Precautionary motives are extended to include internal disequilibrium, mercantilist arguments are shown to interact with capital flows, and institutional views are advanced by integrating econometric results with adequacy benchmarks. Together, the ARDL–UECM framework demonstrates that reserves are shaped simultaneously by trade, capital mobility and monetary imbalances, and that adequacy analysis provides a theory–policy bridge for determining 'how much is enough'.

Comparative Perspective: BRICS vs. India

While this study focuses on India, situating the results within a broader BRICS perspective offers valuable insights. The determinants of reserves among BRICS economies reveal both similarities and divergences. For instance, China has historically pursued a mercantilist strategy, accumulating reserves primarily through persistent trade surpluses and managed ER policies (Aizenman & Lee, 2007). In contrast, Brazil's reserve accumulation has been strongly linked to managing volatile capital inflows, particularly portfolio investments, which parallels India's positive relationship between FPI and reserves (IMF, 2016). Russia's reserves have been influenced heavily by commodity cycles, with oil and gas revenues playing a central role (Ocampo, 2013)—a factor less relevant for India, where imports (API) and external debt pressures dominate reserve dynamics. South Africa, on the other hand, has maintained comparatively modest reserve buffers, constrained by structural current account deficits and ER volatility (World Bank, 2020).

In this context, India's reserve behaviour appears hybrid: like Brazil, precautionary motives against volatile capital flows are important; like China, reserves have exceeded conventional adequacy thresholds; yet, unlike Russia, commodity windfalls are not a driver. This comparative lens underscores that while the BRICS economies share a common interest in building reserves for stability, India's case is distinctive in combining strong precautionary accumulation with a consistent surplus beyond adequacy benchmarks. This reinforces the study's conclusion that India's reserves can be redeployed more productively without compromising external stability.

Policy Suggestions

By 2020, India's reserves far exceeded conventional adequacy norms: they covered 12 months of imports (against the 3-month benchmark), were more than double the STED and stood above 20% of broad money. This indicates the presence of a substantial surplus buffer. Even a modest redeployment of 10%–20% could ease external debt-servicing costs or finance high-return investments in infrastructure, health and education.

These findings yield several important policy lessons for India's reserve management strategy. First, the evidence of persistent reserve surpluses relative to adequacy benchmarks suggests that maintaining excessively high stocks imposes fiscal and opportunity costs. A more efficient strategy would be to deploy a portion of surplus reserves towards external debt reduction, thereby lowering the country's interest burden and improving sovereign creditworthiness.

Second, the results highlight the potential of reallocating reserves to productive domestic investment. Channelling a fraction of reserves into infrastructure, energy security and digital innovation would generate multiplier effects for long-term growth while still preserving sufficient buffers for external shocks. This aligns directly with SDG 8 (sustained and inclusive economic growth) and SDG 9 (resilient infrastructure and innovation).

Third, the significant role of imports, portfolio flows and monetary disequilibrium in shaping reserves underscores the need for integrated macroeconomic management. Policies aimed at stabilising capital flows, managing current account imbalances and deepening domestic financial markets can reduce the volatility that fuels precautionary hoarding. At the same time, strengthening institutional quality and policy credibility would enhance confidence, enabling reserve optimisation without undermining external stability.

Finally, India's reserve management strategy should be situated within the broader agenda of sustainable development and resilience. By linking econometric evidence with adequacy diagnostics, this study shows that reserves are not merely a financial safeguard but also a developmental resource. Their prudent redeployment can free fiscal space for health, education and climate-resilient infrastructure, directly supporting the SDGs while maintaining macroeconomic stability.

Conclusion

Building on the policy insights outlined above, this section summarises the study's key findings, theoretical contributions and implications for future research. This study examined the determinants of India's foreign exchange reserves using quarterly data from 2000 to 2020 within an ARDL–UECM framework. By explicitly incorporating a money market disequilibrium variable, the analysis provided fresh insights into both the long-run and short-run drivers of reserves. The results indicate that imports, foreign portfolio inflows and domestic monetary disequilibrium significantly influence reserve accumulation, with imports exerting the strongest negative effect. Reserve adequacy diagnostics further revealed that India consistently maintains reserves above precautionary thresholds, suggesting the presence of surpluses.

Theoretically, the findings refine the precautionary motive by showing that reserves function not only as insurance against external volatility but also as a corrective mechanism for internal monetary imbalances. They also nuance the mercantilist perspective by highlighting its interaction with capital flows and disequilibrium dynamics, rather than treating it as an isolated motive. Moreover, by integrating econometric results with adequacy benchmarks, the study advances institutional perspectives and builds a bridge between theory and applied policy analysis.

Like all empirical work, this study is subject to certain limitations. The analysis focuses primarily on macroeconomic and monetary determinants, leaving aside political economy factors and global financial integration channels that may also shape reserve dynamics. Future research could extend the framework by incorporating nonlinear effects, comparative evidence across countries and the role of global shocks such as climate risks or technological disruptions.

Acknowledgements

We would like to thank the Department of Economics, University of Kashmir, for their valuable contributions to this study.

Authors' Contribution

Arjumand Qadir conceptualised and designed the study and conducted data analysis. Mohammed Ayub Soudager contributed to the writing and editing of the manuscript.

Data Availability

The data for the said study have been extracted from:

1. www.rbi.org.in
2. www.imf.org

The complete data sets used during the current study are available from the corresponding author on reasonable request.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship and/or publication of this article.

Funding

The authors received no financial support for the research, authorship and/or publication of this article.

ORCID iDs

Arjumand Qadir https://orcid.org/0009-0002-9338-2433
Mohammed Ayub Soudager https://orcid.org/0000-0002-4078-2479

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Appendix A

Table A1. Results of Unit Root Test.

	ADF Statistic						PP Statistic					
	With Constant		With constant & Constant & Trend		Without Constant		With Constant		With constant & Constant & Trend		Without Constant	
Variables	Level	Δ	Level	Δ	Level	Δ	Level	Δ	Level	Δ	Level	Δ
Lnm3	−2.75	−2.95*	−0.99	−3.96*	2.35	−1.48*	−7.10**	−9.25**	−0.74	−14.41**	7.70	−5.65**
Lngdp	−1.37	−8.65**	−3.98*	−8.76**	5.59	−2.02*	−0.62	−14.58**	−3.87	−15.35**	7.55	−9.91**
Lner	−0.02	−6.97**	−1.96	−6.98**	0.98	−6.80**	−0.27	−6.97**	−1.76	−6.97**	1.67	−6.77**
r	−1.67	−11.15**	−1.62	−11.16**	−1.05	−11.16**	−1.62	−11.04**	−1.57	−11.05**	−1.09	−11.04**
Lnir_gdp	−1.89	−9.84**	−2.21	−10.11**	−6.0**	−3.71**	−1.89	−9.80**	−2.19	−10.08**	−6.27**	−7.75**
Lapi	−1.76	−8.26**	−0.75	−8.56**	−2.53*	−7.87**	−1.74	−8.26**	−0.74	−8.62**	−2.46*	−7.87**
Lfpi_gdp	−1.73	−11.13**	−1.91	−11.12**	−1.41	−11.00**	−2.25	−20.97**	−4.69**	−21.78**	−1.24	−19.16**
Lsted_gdp	−1.73	−8.46**	−0.91	−8.65**	−2.23*	−8.07**	−1.72	−8.45**	−0.93	−8.65**	−2.22*	−8.10**
oc	−2.89*	−13.20**	−2.90	−13.16**	−0.56	−13.28**	−3.70**	−13.32**	−3.67*	−13.56**	−0.69	−13.40**

Notes: Δ refers to first difference.
* and **: Statistically significant at 1% and 5%, respectively.

Appendix B. Stability Diagnostics

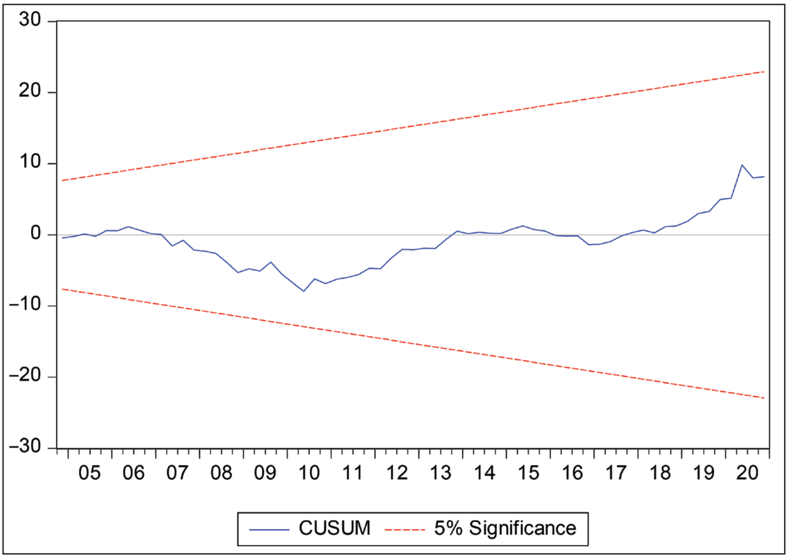

Figure B1. CUSUM Test for Long-run Money Demand Function.

Note: The CUSUM statistic remains within the 5% significance band, confirming stability of the estimated coefficients.

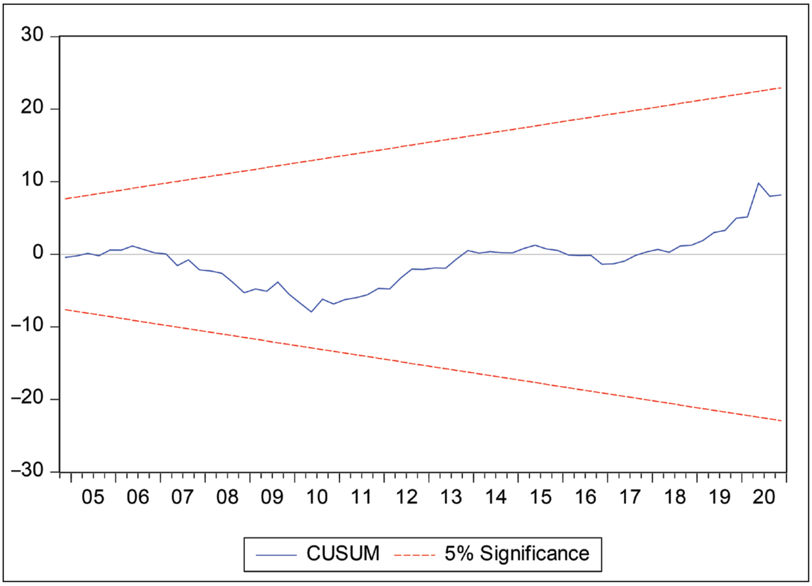

Figure B2. CUSUM Test for Long-run Reserve Demand Function.

Note: The CUSUM statistic stays well within the critical bounds, indicating stability of the reserve demand function estimates.

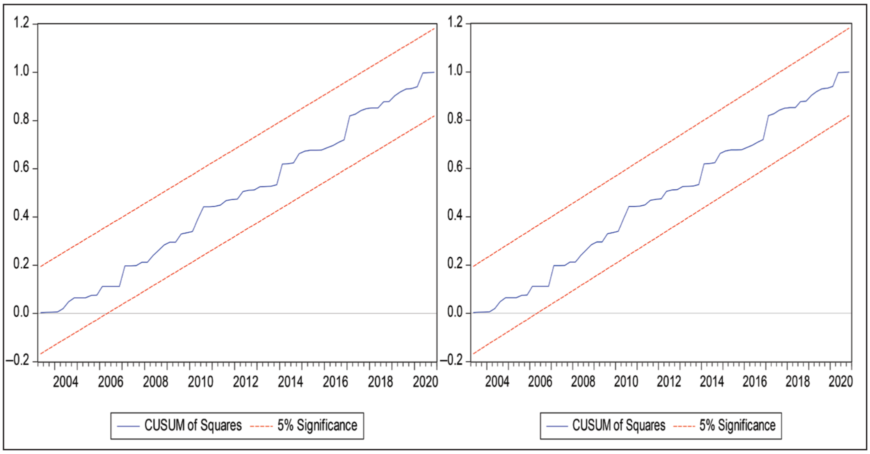

Figure B3. CUSUM of Squares Test for Long-run Money Demand.

Note: The CUSUMQ statistic lies within the 5% significance bands throughout the sample period, suggesting parameter constancy and absence of structural breaks.

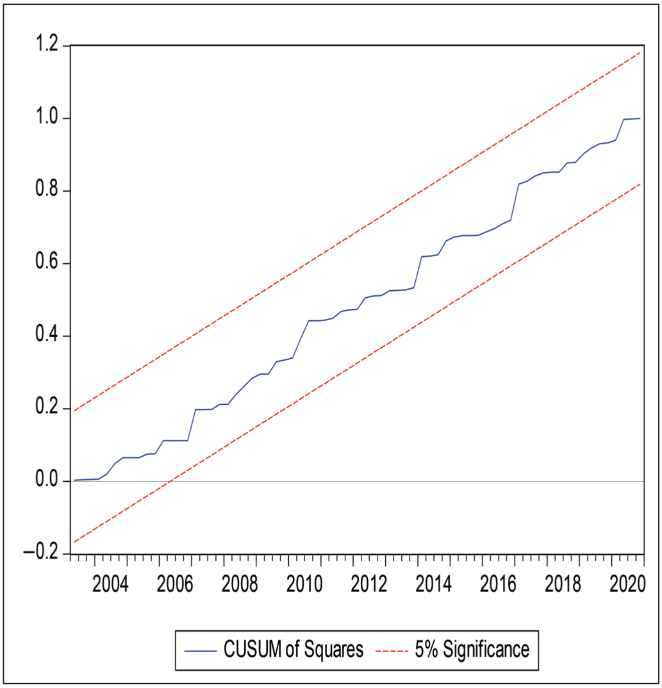

Figure B4. CUSUM of Squares Test for Reserve Demand Function.

Note: The CUSUMQ statistic lies within the 5% significance bands throughout the sample period, suggesting parameter constancy and absence of structural breaks.

Artificial Intelligence and Machine Learning in Our Everyday Life: Uses, Problems and Future

GLIMS Journal of Management Review and Transformation
4(2) 161–177, 2025

DOI: 10.1177/jmrt.251398199
mrt.greatlakes.edu.in

Jogen Sharma[1] and Dayawanti Tarmali[2]

Abstract

In recent years, artificial intelligence (AI) and machine learning (ML) have developed at a very high pace, transforming numerous areas of modern life. Such technologies are becoming increasingly widespread in the context of daily life in healthcare (to diagnose and monitor) and finance (to detect fraud and provide personalised services), smart homes (via voice assistants and automation), education (via AI tutors and personalised learning), transportation (with route optimisation and new self-driving vehicles) and entertainment (with recommendation systems and content creation). Individuals and organisations are assured of efficiency, customisation and automation through such applications. Nevertheless, the massive use of AI comes with serious concerns: the privacy of data, the fairness and transparency of algorithms, the elimination of biased or discriminatory results and the impact on the workforce in the form of reskilling. Therefore, it is important for them to be innovative and responsible. This article is a review of the recent literature on AI/ML in everyday life, a comparison of its adoption in different sectors and an analysis of ethical issues. A bibliometric approach is described, and existing use cases are described on a domain-by-domain basis. We balance the advantages, obstacles and comments on the policy implications. Finally, future paths, including generative AI, edge computing and sustainable AI, are discussed, and it is noted that ethical governance is needed. Combined, both these thorough reviews indicate the revolutionary potential of AI in our daily lives and the significance of its application in a responsible manner.

[1] India International Centre, New Delhi, India
[2] Management Development Institute Murshidabad, West Bengal, India

Corresponding author:
Jogen Sharma, India International Centre, New Delhi 110003, India
E-mails: jogen.sharma2@gmail.com; jogen.sharma@zohomail.in

Keywords

AI, ML, implementation into everyday life, robots, ethical AI, intelligent technology

Submitted 28 September 2025; accepted 27 October 2025

Introduction

Artificial intelligence (AI) is the use of computer systems to carry out functions that would otherwise involve intelligence on the part of a human being. Machine learning (ML) is a subset of AI that allows computer systems to become better with experience. These technologies have been developed over the years, with progress in algorithms, availability of data and processing power, which have made them quick to implement in both consumer and enterprise environments. Intelligent machines have already penetrated ordinary reality, such as smartphone applications, home assistants, online services and industrial systems. For example, smart thermostats, voice assistants and smart appliances can change depending on how people live. AI can be used in healthcare to facilitate accurate diagnosis and individualised treatment planning. Individually designed learning is assisted by AI-based platforms. Self-driving and logistics are transforming the transportation sector and voice-activated chatbots, while gaming AI and stream recommendations are transforming entertainment. Such developments have led to the expansion of the AI market, which is expanding exponentially worldwide. In 2025, the AI industry was estimated to be worth over 515 billion and is expected to have a compound annual growth rate of almost 20% to some 2.74 trillion in 2032. This massive expansion underscores the fact that AI is becoming increasingly embedded in the industry (Figure 1). The use of AI/ML is becoming more widespread, providing productivity improvement, personalised services and automation benefits.

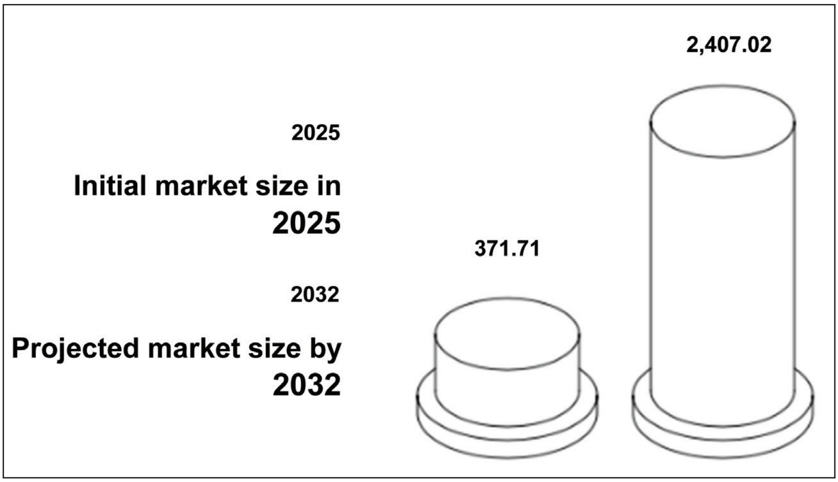

Figure 1. Global AI Market Size (2025–2032).

Along with these opportunities, some questions regarding ethics and practicality have arisen. AI systems are based on massive data sets and are a matter of concern, as well as privacy and personal information security. When algorithms are trained using biased or incomplete data, they will provide biased or discriminatory predictions, which will continue to perpetuate social inequities. Additionally, automation poses the risk of replacing some jobs as it introduces new positions and requires a labour force to upskill. Responsible AI implementation must therefore deal with data governance, transparency and impact on society. Here, our review restricts the existing applications of AI/ML to the real world and underscores the issues of ethics. We use a methodical approach for the literature review to chart the new studies (2018–2025) on AI in daily life to help generalise the knowledge across industries and shape the prospects.

Literature Review

The implementation of AI/ML in diverse real-life situations has been widely explored in recent literature, revealing a strong interest in its opportunities and fears of pitfalls. Many reviews have demonstrated the application of AI in medical imaging, medical diagnostics, telemedicine and wearable monitoring. For example, deep learning algorithms can examine radiology pictures with high precision, and wearable sensors based on AI can notify individuals about illnesses. Researchers have reported that AI tutoring and adaptive learning platforms are changing pedagogy through tailored content and pace for current students. According to the records of finance researchers, the system of fraud detection and robo-advisors is built on ML models to enhance security and financial planning. Research on smart homes and IoT states that the use of appliances, voice agents and smart thermostats has become widespread and automates the process of controlling home and energy consumption. In transport, AI allows optimisation of routes, and autonomous vehicles are the focus of research, but their complete implementation is not yet possible owing to technical and regulatory challenges. Recommendation engines and content-generation tools in both entertainment and social media outsource much of the experience and enable new creative uses. In these areas, hands-on research tends to point out improvements in effectiveness and convenience, and discusses early adoption.

Comparative results show disproportionate AI adoption by industry and company. A working paper by NBER concludes that, at the time (2017), less than 6% of US firms had implemented AI-related technologies. The adoption rate is also concentrated among large businesses: approximately 50-60% of very large companies employ AI compared to only approximately 6% of small companies. Some of the industries are pioneers—manufacturing, information services and healthcare—and approximately 12% of the companies had employed AI, but other industries, such as construction and retail, had just around 4%. Figure 2 shows the inter-sectoral variation in the intensity of AI integration. It was found that very large companies (in particular, in technology-driven industries) report using AI to perform tasks, such as predictive maintenance and data analytics, but small or traditional industries are lagging. Such research shows the digital divide: AI penetrates every industry but unequally, which may imply the obstacles of cost, access to data and necessary experience.

Another key thematic area in the literature is ethical consideration. The issue of algorithmic bias—the inclination of AI systems to give unfair results when conditioned on biased data—has been raised by researchers. An example of this is a study of AI hiring tools, which adds that in case the historical data used to predict an automated hiring algorithm echo previous biases, the algorithm may reproduce or increase discrimination by gender or race. In wider terms, algorithmic bias can be viewed as systemic and repeatable errors in computer systems that cause unfair discrimination based on protected characteristics. A number of case studies record bias in areas such as criminal justice risk assessment, facial recognition and loan approvals, where precaution is not observed. Equally, privacy and security issues dominate the literature on AI in healthcare, as one of the CDC reports cautions, with the capacity of AI to handle large volumes of personal information, patient privacy and confidentiality being the foremost concerns in healthcare AI. When sensitive data are leaked or misused, trust in services operated by AI will be destroyed. Furthermore, researchers mention the social consequences of automation: AI can replace ordinary professions and consequently increase the need for technical positions, which will require mass upskilling of the population and the development of policies. Overall, the current literature shows the potential of AI to improve performance under real-life conditions and the importance of considering the aspects of fairness, accountability and human effects.

However, there are still gaps in practice-based research. Other reviews note the necessity of conducting additional longitudinal research on the effectiveness of AI-based interventions in the real world and providing more effective measures of ethical compliance (e.g., open audits of algorithms). We observe that, as numerous articles speak about the advantages of AI in particular sectors, there are fewer overall cross-sector comparisons or syntheses of the experience of everyday users of AI. This drives us to combine cross-domain knowledge and actively compare the advantages of the application with the overall challenges and issues of governance.

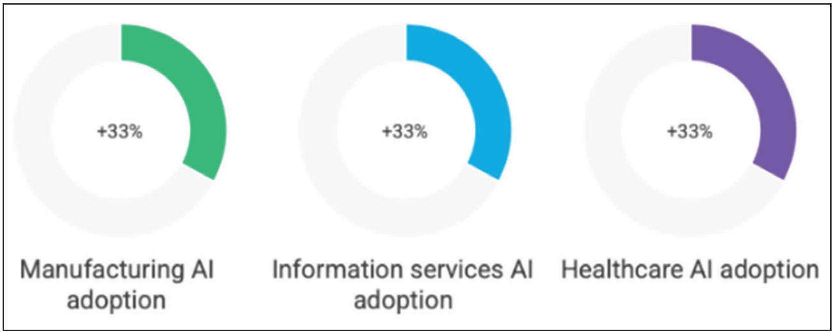

Figure 2. The Intensity of AI Use and Testing Rates by Sector (United States).

Methodology

Mixed bibliometric and thematic review methods were used in the study. We selected peer-reviewed articles, conference papers and technical reports published between 2018 and early 2025 in large academic databases (e.g., Scopus, Web of Science, IEEE Xplore and Google Scholar) through a systematic search. Search strings were a combination of terms such as AI, ML and keywords of target fields (healthcare, education, finance, smart home, transportation and entertainment) and ethical terms (privacy, bias and governance). The inclusion criteria were based on studies providing empirical data or substantive analysis on AI/ML application in everyday life and literature reviews about the theme. The exclusion criteria were limited to purely technical articles in the absence of a practical situation.

Based on these searches, we were able to retrieve more than 500 documents. After deduplication and relevancy screening, 100 of the most important sources were chosen for in-depth analysis. We also incorporated official guidelines (e.g., UNESCO AI Ethics Recommendation) and official reports on the subject by authoritative institutions (e.g., Future of Jobs 2023 by the World Economic Forum). Co-authorship networks and keyword trend maps were plotted using bibliometric tools (VOSviewer and Biblioshiny), and clusters of research topics were identified (not shown here). Qualitative analysis grouped the results based on the field of application and ethical/policy themes. We have taken statistics (e.g., adoption rates and market values) out where available to show trends. Trends were calculated using Matplotlib, and embedded screenshots of corresponding charts of reputable sources were used to create the visualisations. This approach enabled us to generalise wide-ranging knowledge in various fields and base our discussion on quantitative data from recent studies and reports.

Uses of AI and ML in Our Life

Healthcare

AI and ML are revolutionising the healthcare sector by being applied in the fields of diagnostics, treatment planning and patient monitoring. Deep learning algorithms are used to process medical images (X-rays, MRIs) to identify anomalies (e.g., tumours) with similar accuracy to that of trained human experts. AI chatbots have been embraced in telemedicine platforms used for triage and care planning (Kumar et al., 2025). Smart watches and similar fitness trackers use ML to track vital signs (heart rate and glucose levels) and notify users or physicians when these values are abnormal. Research has demonstrated that AI has the potential to forecast the risk of an illness based on mining lifestyle and genetic information. For example, personalised AI systems can be deduced based on the logs of diets and sleep patterns of a person at risk of diabetes or heart disease. In addition, AI-based genomic studies facilitate precision medicine, in which treatment is tailored to patient subtypes. Such AI tools can enhance results through early detection of conditions and personalised care. Nevertheless, researchers warn that AI suggestions should be used to supplement (Dangeti et al., 2023) (not substitute) expert guidance and that effective data privacy measures are required to secure vulnerable medical data.

Education

AI/ML can promote personalised learning and tutoring in education. Adaptive learning platforms analyse the mastery of a student by adjusting the level of difficulty of the content in real time using algorithms. As an illustration, intelligent tutoring systems can correlate the results of quizzes and give each learner exercise tailored to the results. Automated marking of some assignments is also done by AI, allowing teachers to concentrate on teaching (Kamalov et al., 2023). Recent research indicates that AI-personalised learning can boost student participation and retention (e.g., increasing course completion rates by up to 70 points) to a considerable degree (e.g., 23). Moreover, natural language processing enables AI tutors to talk to students and respond to questions or explain any concept in real time. These applications are promising; however, teachers insist that human intervention is necessary (Almusaed et al., 2023; Mouta et al., 2024; Webb et al., 2020). The issues surrounding this area are the promotion of educational equity (AI-driven programmes must benefit all groups of students equally) and training teachers to work with AI tools. According to the literature, institutions must incorporate AI literacy into teacher training because many teachers have not been trained to do so.

Finance

Such financial services have utilised AI to accomplish activities, such as fraud detection, risk assessment and customer service. Unlike conventional rule-based systems, ML algorithms scan transaction data on the fly to identify suspicious behaviour (e.g., suspicious payments) (Anang et al., 2024; Buchanan, 2019; Weber et al., 2023). Robo-advisory applies AI to provide individualised investment money based on the interests and risk-taking of an individual. It is important to note that according to a survey of financial institutions, 88% of the organisations that use AI indicate a rise in revenue as a result of AI tools. In fact, 34% of such firms experienced an increase of more than 20%, and over 50% saw an increase of at least 10% in revenues (Figure 3). These enhancements are due to efficiency (e.g., quicker processing of loans), improved decision-making and additional services. Chatbots can also be used to manage customer queries 24/7 and help reduce bank waiting times.

This pattern demonstrates how financial automation and analytics based on AI (e.g., fraud detection, algorithmic trading and personalised advisory) are turning into real business value.

However, finance is also subject to ethical problems. The AI-driven credit score should not be biased by race or income (to allow regulators to provide loans

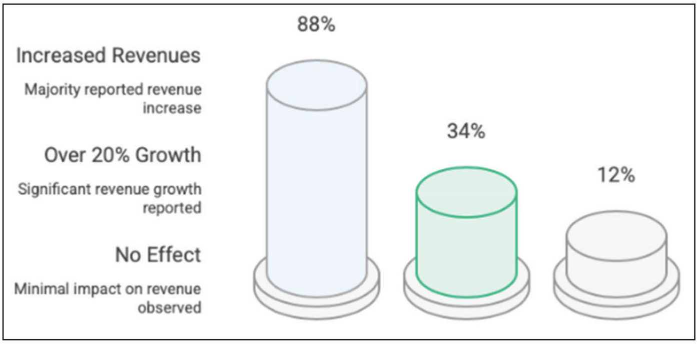

Figure 3. AI Effect on Financial Services Revenue.

impartially). Privacy is important when algorithms are fed personal financial records (Cao et al., 2024). In addition, job changes are also a matter of concern. For example, algorithmic trading can eliminate certain positions of traders and generate the need for data scientists and compliance specialists.

Smart Technology and Homes

The use of AI-powered smart home devices has become more widespread. Voice assistants (e.g., Alexa, Google Assistant and Siri) are voice-controlled light, thermostats and appliance controllers. Intelligent sensors can be trained to perform routines (e.g., setting the thermostat automatically) and conserve energy. AI is used in entertainment devices (smart TVs and streaming gadgets) for content suggestions. A recent report also indicates that 45% of households in the United States own at least one smart home device, and 18% of households own six or more. Adoption keeps increasing annually: it is estimated that in 2022 the number of homes in the United States that utilised smart devices was 57.6 million (Geng & Bi, 2023; Jois et al., 2023), and this number is expected to increase to approximately 85 million by 2026 (Figure 4).

This is reflected in global consumer IoT markets. Smart home/IoT devices were expected to grow to approximately 26 billion by 2022, which is expected to rise to approximately 30.9 billion by 2026 (Figure 5). AI infiltration in everyday reality is emphasised by the delivery of interconnected devices (e.g., wearables and voice assistants). For example, voice assistants are used individually by hundreds of millions of people. In 2022, approximately 142 million Americans (45% of the population) utilised voice AI, and the figure is increasing. Significant platforms are naming an increasing number of users; for example, Google Assistant has overtaken 88 million users in the United States alone.

Voice assistants are worth mentioning as exemplary smart home AI. These systems can not only play music or provide reminders but also connect with other services (banking and e-commerce) by voice. Their development is an example of the normalisation of AI: in 2022, almost three-quarters of Americans actively used

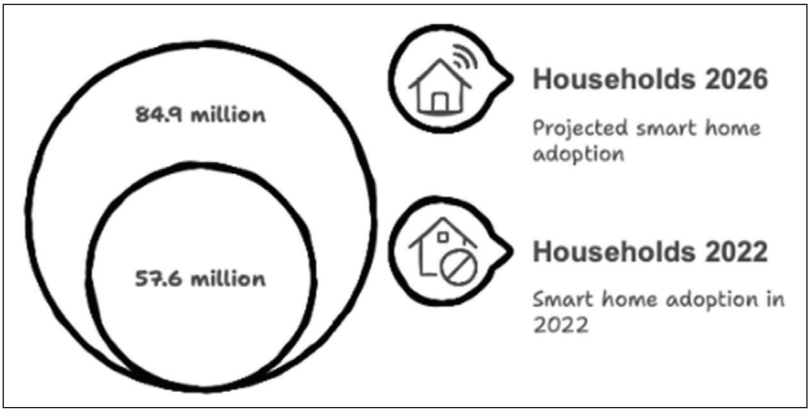

Figure 4. US Households Using Smart Home Devices (2022–2026).

voice assistants. This human–machine interface makes life more convenient (e.g., hands-free operation) but raises concerns over voice data privacy and voice recognition accuracy.

Transportation

The use of AI and ML transforms transportation by optimising and being autonomous. ML algorithms can be used in ride-sharing and navigation applications to estimate demand, obtain optimal routes and reduce waiting time. Traffic management systems are fitted with AI-powered projections that modify signals to relieve congestion. In the logistics industry, AI is used to plan and route a delivery fleet to conserve fuel. One of the most noticeable fields is that of autonomous vehicles: organisations such as Waymo and Tesla implement AI vision and decision-making solutions to allow self-driving on a highway. These mechanisms combine lidar-based sensor fusion (lidar, cameras, GPS) and deep learning-based real-time environment perception. However, autonomous vehicles that are entirely independent face technical and social challenges. Existing systems are effective in the presence of clear weather, yet managing unexpected incidents (e.g., extreme weather and nonstandard road users) will continue to be problematic. Another reason why autonomous vehicle deployment is not widespread is regulatory uncertainty and concerns regarding public safety. Therefore, although today AI is certainly contributing to the planning of the route and helping each driver, the fully autonomous transport remains a novel region.

Algorithmic Bias and Fairness

AI may inadvertently contribute to the reinforcement of social prejudice. Models can be trained with historical data that represent human prejudices and thus can

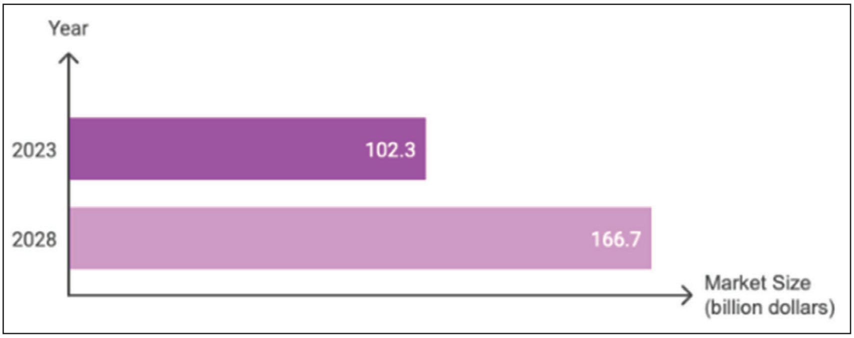

Figure 5. Global Smart Device Market Growth (2023–2028).

disproportionately harm the members of the protected classes. For example, an AI recruitment system trained on previous hiring could give lower scores to candidates who are not part of the majority group based on previous hiring trends. This type of algorithm bias causes injustice in lending, hiring, policing and so on. Various training data and bias-detection methods are required to mitigate these issues. Scholars have promoted the idea of auditing the disparate impact and incorporating stakeholders into the design process to ensure fairness.

Job Displacement Versus Skill Transformation

Automation is a cause for concern not only because it eliminates jobs but also because it introduces new technical positions. A recent report by the World Economic Forum estimated that there will be a net decline in employment of approximately 14 million (2% of the current jobs) by 2027 caused by disruptive technologies (Bühler et al., 2022; Santos & Oliveira, 2020; Tuomi et al., 2020). However, 69 million new jobs are anticipated. Specifically, the skill requirements of analytical thinking and AI and big data are on a rapid increase. Indicatively, 42% of enterprises will invest in AI/data skills training by 2027. Such a churn implies that employees in more humdrum positions could be laid off, and there will be increased pressure on AI specialists and managers capable of managing AI systems (Fuentes-Peñailillo et al., 2024; Holm et al., 2023; Istudor et al., 2024). Therefore, reskilling the workforce is a challenge for policymakers and educators. Some studies have indicated that phased transitions and high social safety nets can mitigate the effects of displacement.

Ethical Governance and Accountability

The adoption of AI poses a social concern. Who bears the responsibility of a harmful decision made by an AI? Is there transparency in the black-box models? International organisations have reacted; for example, the 2021 Recommendation on the Ethics of AI by UNESCO has its focus on protecting humanity, its transparency and human control over AI (Morandín-Ahuerma, 2023; Saikanth et al., 2024). The literature emphasises the importance of strong governance structures and principles (e.g., fairness certifications and impact assessments). The adoption of corporate ethical policies (diverse design groups, ethics boards, etc.) is commonly recommended (Hirvonen et al., 2023). External audits are typically recommended. It is generally agreed that while innovation should be encouraged, stringent accountability measures should also be taken to ensure that innovation is not abused or hurt society.

There is a relationship between the two. For example, AI bias can be addressed by educating more people on AI and engaging more diverse perspectives in the process, whereas privacy-conscious architectures can minimise the risk of data exposure. Overall, consideration of these issues is urgent to achieve the maximum benefits of AI without harming trust or equity.

Show Business and Social Media

AI is part of digital entertainment. In video games, AIs manage nonplayer characters and adjust the difficulty of the game. Recommendation algorithms depend on movie and music platforms (Netflix and Spotify) to personalise content. Social media feeds apply ML to show posts that you will probably want to read. Notably, generative AI (text, image and video synthesis) produces novel types of creative tools and even automatic content generation (e.g., AI-generated scripts or artwork). The entertainment AI sector is a fast-gaining market; it is estimated to be worth between US$15b and US$196b by 2024 to 2033, respectively (Ooi et al., 2023). One third of the value of this segment is achieved only through personalised recommendations, indicating consumer interest in personalised experiences.

Difficulty and Ethical Issues

With the permeation of AI/ML in daily life, some problematic issues have become commonplace.

Data Privacy and Security

AI systems require large amounts of personal data. These data are important and must be secured to avoid breaches. For example, the privacy stakes for gathering health or financial data on ML are high. Researchers emphasise privacy and confidentiality protection because AI has a taste in the data. Laws such as GDPR and HIPAA are starting to address these problems, but they must be continuously monitored, particularly as devices continue to expand (Buchanan, 2019). Companies should enforce effective encryption, anonymisation and consent procedures on the part of users.

Algorithmic Bias and Fairness

AI may offset social bias. In scenarios where the models are trained using historical data of human biases, they can disproportionately harm the members of the protected classes (Liu, 2024). For example, an AI-based hiring tool that was trained on previous hires may prioritise candidates of minority groups at a lower rank than the historical pool and is unbalanced. The results of such algorithmic bias include unfair lending, hiring, policing and so on. To mitigate these problems, training data and various bias-detection methods are required. Scientists recommend that algorithms be audited due to disparate impacts, and design-time stakeholder involvement should be implemented to maintain fairness.

Job Displacement Versus Skill Transformation

Automation is also associated with job destruction, although it leads to new technical jobs. According to a recent report by the World Economic Forum, it is predicted that the number of net jobs lost (2% of existing jobs) to disruptive technologies will reach approximately 14 million by 2027. However, 69 million new jobs are anticipated. Specifically, the domains of analytical thinking and AI and big data are fast becoming a growing skill requirement. To illustrate this point, 42% of firms intend to invest in AI/data skills training by 2027. This churn implies that employees with fewer professional jobs can be laid off, whereas there is a higher demand among AI experts and managers capable of controlling AI systems. Therefore, the challenge of reskilling the workforce has been presented to policymakers and educators. Phased transitions and high social safety nets are proposed by some of the literature to mitigate the effects of displacement.

Ethical Governance and Accountability

The introduction of AI has created general societal questions. When an AI makes a destructive decision, who holds an accountable party? Is it possible to guarantee the transparency of black-box models? The international community has reacted, such as the 2021 Recommendation on the Ethics of AI by UNESCO, which focuses on human rights protection, transparency and human control of AI systems (Laat, 2017). The future EU AI Act is aimed at high-risk applications of AI (e.g., biometrics and critical infrastructure) under stringent conditions. However, patchwork guidelines continue to exist worldwide. The literature emphasises the importance of effective governance systems (e.g., fairness certifications and impact evaluation). External auditing and promotion of corporate ethical policies (diverse design teams and ethics boards) are common suggestions. It is widely agreed that innovation should be approached with a balance in which robust accountability standards are set to ensure that its misuse is avoided and that it does not harm society.

These problems are connected. As an illustration, AI bias can be addressed by increasing diversity in the development process through an improved understanding of AI, whereas privacy-conscious designers can lower data security threats. Overall, these issues must be addressed to achieve the full potential of AI and not compromise trust or equity.

Discussion

Our review confirms that AI/ML has both significant benefits and serious concerns. On the one hand, productivity and innovation are propelled by efficiency gains, personalised experiences and new capabilities in domains (including those discussed in the fourth). Through early detection, AI in healthcare can save lives, AI in education can enhance learning results, smart home AI can minimise energy consumption and add comfort, and financial AI can raise the safety and availability of services. This goes hand in hand with an emerging literature consensus that AI is a 'catalyst to economic growth', which is manifested by its rapidly growing market size and competitive benefits reported by companies.

Conversely, the issues discussed in the fifth section present an acute dilemma. For example, although smart devices gather data to understand user preferences (convenience), they also gather personal data, making them vulnerable to security threats. Although AI tutors have the potential to enhance education, they can also exacerbate the digital divide by discriminating against students who lack access to the internet. This dual nature has been observed in the literature in all disciplines. As Chen et al. (2022) observed, AI can analyse data faster and more comprehensively than humans, but the choices made by AI are influenced by the data it is initially presented with as input. That is, the objectivity of AI can be as great as that of its inputs.

Our results are in line with those of previous surveys and policy analyses. To illustrate, the CDC (2024) states that AI needs to promote equity by not expanding disparities, and the WEF (2023) states that reskilling is necessary as digital adoption grows. We go further with these findings and narrow down to everyday life contexts, gathering evidence across several sectors. In places where the literature tends to deal with particular sectors individually, our synthesis focuses on cross-cutting themes (e.g., privacy issues in both healthcare and smart home contexts).

This synthesis has policy implications; it indicates that regulators must use holistic AI approaches instead of rules that are siloed. For example, AI devices in homes and data-driven medical AI should be encompassed by privacy law. Workforce development programmes must be across industries that are likely to be affected by AI. Our results confirm the need to regulate AI interdisciplinarily, that is, with technical norms (to ensure fairness and robustness) and, at the same time, with social policies regarding education and work.

Finally, we observed certain limitations. Much of the available research is either qualitative or short-term. Empirical research on the effects of AI on society is scarce, both longitudinal and large-scale (Rejeb et al., 2022). The effects of many emerging technologies (e.g., generative AI) may not be well understood in the long term, as they will develop after 2023. We also depend on published literature in our review, and this might not reflect proprietary best practices in the industry. However, we offer a current overview of this knowledge by discussing the most recent peer-reviewed and industry-based sources.

Future Directions

Moving forward, the role of AI in everyday life is determined by several trends. Perpetual AI (e.g., large language/image models) is opening up new possibilities such as AI-generated media and educational contexts. AI-based features, such as AI tutors who can provide you with a unique explanation, or news websites written with AI assistance, will spread. The high growth forecasts of the entertainment industry (Figure 6) can also be attributed to the influence of generative and recommendation AI (Neugnot-Cerioli & Laurenty, 2024).

Other trends include edge AI and on-device intelligence. Instead of using cloud data centres, additional AI will operate on smartphones, home appliances and vehicles (edge computing). This can enhance privacy (data remains local) and decrease latency. For example, smartphones are becoming increasingly capable of performing on-device image recognition or speech processing. Small-ML and wearable IoT research is underway on tiny ML-based AI chips with energy efficiency. Such decentralisation implies that AI can assist in real-time applications (e.g., instant translation or health monitoring) and does not need to be connected to the internet at all times.

Cooperation between humans and AI will become more profound. Many future systems will not be completely autonomous and will instead be used to enhance human capability. In education, we imagine AI teaching assistants that assist teachers in personalising classes. In the medical profession, AI will serve as a second opinion to physicians but not to substitute them. According to the World Economic Forum, machines already perform 34% of business tasks, and

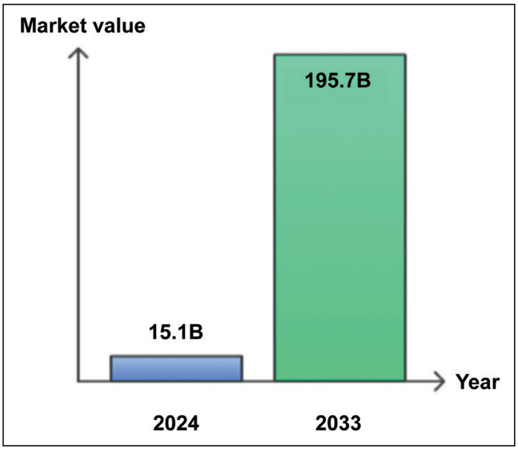

Figure 6. Predicted AI Development in Media and Entertainment (2024–2033).

in the future, routine work will become more automated (Anthes, 2017) (especially information processing), and creative and empathetic work will remain a human prerogative. A major line of research is the development of interfaces and tools that facilitate smooth collaboration (e.g., explainable AI and intuitive dashboards).

AI should be able to develop sustainably and ethically. It is increasingly recognised that AI models are large energy (carbon footprint) consumers, meaning that future AI can focus on efficiency. Additionally, with the proliferation of AI, researchers need to ensure that the present is inclusive, for example, gathering more varied training data and engaging ethicists in design. The UNESCO Recommendation is a framework, but it requires that education and institutional support be made a reality. Governments and industry leaders are expected to invest more in the research and regulation of AI ethics in the years ahead.

Lastly, AI will continue to be integrated into our everyday lives with new developments, such as AI-assisted biotechnology, robotics integration (household robots) and smart city infrastructure. They all involve new difficulties (legal and social) that require interdisciplinary research (Adewusi et al., 2024; Huang et al., 2022; Loureiro et al., 2020). To conclude, the future of AI implies increasing power, but also the need to have responsible AI inventions that actively consider privacy, justice and human values. Subsequent efforts must monitor the results of AI applications and optimise the best practice to ensure that technological advancement is not counteracted by the well-being of society.

Conclusion

As discussed in this article, AI and ML infiltrate nearly all areas of life: personalised healthcare and educational systems, intelligent homes and smarter transportation. Evidence testifies to the obvious positive outcomes: the increase in productivity, the convenience factor and the new services, in which cost-effectiveness translates into economic gains (as with the multi-trillion-dollar market forecasts). However, such profits are accompanied by significant limitations. Essential issues such as personal data protection, elimination of algorithmic bias, workforce transition in place and ethical governance cannot be disregarded. The synthesis of our research underlines the importance of a balanced solution: further innovation also needs strong ethical norms and policies (restating ESCO's request to make AI human-centric). Through a critical analysis of both arguments, this article points out that the ultimate outcome of AI application in society depends on the responsible integration of AI. In the future, the relationship between technologists, policymakers and citizens will be necessary, as it is the only way to ensure that AI potential does not worsen life, but improves it without damaging trust and fairness.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship and/or publication of this article.

Funding

The authors received no financial support for the research, authorship and/or publication of this article.

ORCID iDs

Jogen Sharma https://orcid.org/0000-0001-7151-0137
Dayawanti Tarmali https://orcid.org/0009-0001-0159-8505

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Empirical Research

Revisiting the Poverty: Economy Relationship—Evidence from Selected Central Asian Countries

GLIMS Journal of Management Review and Transformation
4(2) 178–194, 2025

DOI: 10.1177/jmrt.251375614
mrt.greatlakes.edu.in

Shahid Mohammad Nengroo[1], Imtiyal-ul-haq[2] and Suadat Hussain Wani[3]

Abstract

The present study attempts to examine the relationship between economic growth and poverty in Central Asian countries for the period 2000–2020. To achieve the objectives of the study, time series autoregressive distributed lag (ARDL) has been applied. The study confirms a cointegrating relationship among the variables across the countries. From the results, it can be concluded that financial development and economic growth have a positive impact on poverty reduction. This finding gives credence to the trickle-down effect of growth on the poor. However, the positive relationship between inequality and poverty suggests that inequality raises poverty by reducing economic development in all these countries. Furthermore, evidence from Kazakhstan and Kyrgyzstan indicates that inflation lowers poverty through decreased labour expenses, which in turn raises employment levels in these nations.

Keywords

poverty, inequality, economic growth, Central Asian countries, ARDL

Received 12 August 2025; accepted 20 August 2025

[1] Centre of Central Asian Studies, University of Kashmir, Srinagar, Jammu and Kashmir, India
[2] Department of Economics, University of Kashmir, Srinagar, Jammu & Kashmir, India
[3] Centre for Distance and Online Education, University of Kashmir, Srinagar, Jammu and Kashmir, India

Corresponding author:
Shahid Mohammad Nengroo, Centre of Central Asian Studies, University of Kashmir, Hazrattbal, Srinagar, Jammu and Kashmir 190006, India.
E-mail: Shahidmohammad1162@gmail.com

Introduction

In 1991, centrally planned economies in the former Soviet Union collapsed, relinquishing newly independent states—especially countries in Central Asia—to chase their way of post-communist economic transformation. Like other erstwhile Soviet republics, countries in the Central Asian Region (CAR) initially seemed to be fairly farsighted for transition towards a market-based economy. To some extent, they have performed well in the industrial and agricultural sectors. Some of these nations were also endowed with substantial natural resources, particularly with oil and other mineral reserves. Similarly, the labour force was relatively well educated and skilled (Campos & Coricelli, 2002). However, with the passage of time, these countries were not able to perform well as compared to Eastern European countries in terms of growth, poverty reduction, inequality, unemployment and other related problems. Figure 1 complements this argument as it indicates the relationship between income (GDP per capita) and poverty incidence (HCR as measured by $2.15 per day). Particularly, it shows that higher income levels are associated with a decline in poverty over time as some countries, including Finland, Belarus and Kazakhstan, have experienced higher income levels and a negligible incidence of poverty. In the case of Central Asia, many countries have experienced a negative association between income and poverty. However, Turkmenistan and Tajikistan have experienced lower income levels and higher poverty incidence over time.

It is important to mention here that with the passage of time, many countries of CAR have experienced heavy dependence on oil, natural gas, mining exports and remittances from migrant workers to accelerate their economic growth (Poghosyan, 2022). Further, the region observed a lack of economic diversification. Such an orientation has made these nations vulnerable to large external shocks in commodity prices, particularly in oil and natural gas, which transmits uncertainty to other sectors of the economy. These nations experienced more difficulty

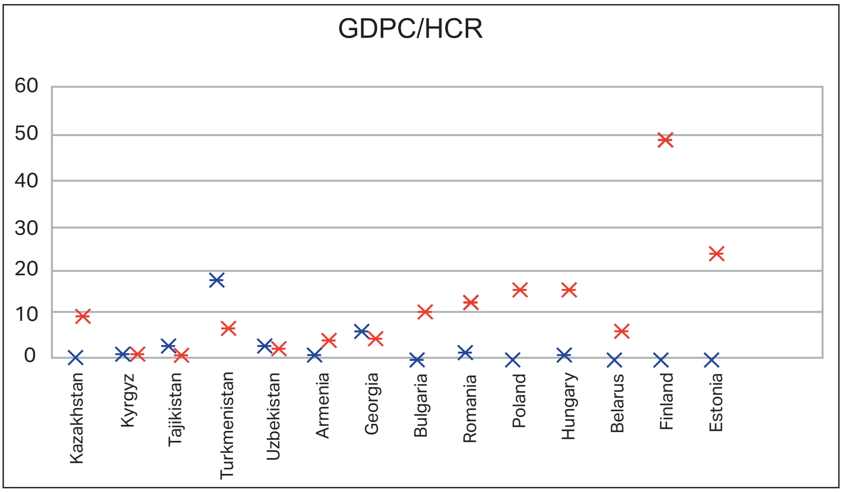

Figure 1. Income Levels and Poverty (2020).

Source: World Bank (2023).

compared to other transition economies in shifting from a planned to a market economy. For instance, commercial and transportation channels that these landlocked countries had historically capitalised on were disrupted. Similarly, the budget transfers from Moscow abruptly stopped after independence. Further, the main problem in earlier times was of brain drain, with over a million Russians, many among them were highly skilled specialists, leaving Central Asia after its independence. It was due to this situation that the wave of economic reforms progressed at a slow pace across the region. The impact of all these factors was that the changeover was accompanied by widespread job losses, rapid economic collapse, extremely high inflation rates and a severe drop in real wages. Even in present times, poverty-related issues are increasing across the region.

A look at economic conditions in the region shows that Kazakhstan is one of the leading producers of crude oil and natural gas. The country possessed 5.12 metric tons (mt) of oil and natural gas in 2000, 79.2 mt in 2010, and 85.7 mt in 2020. The per capita GDP (at current prices) has increased from $1129 in 2000, $9070 in 2010, to $9172 in 2020 (World Bank, 2023). The economy falls under the category of upper-middle-income countries. The New Silk Route is also adding to its growth and development potential.

The world's fourth-largest natural gas reserves are found in Turkmenistan. The country also possesses substantial oil resources and is one of the leading producers of cotton. The per capita GDP (at current prices) has increased from $635 in 2000, $4,286 in 2010, to $7,946 in 2020 (World Bank, 2023). The government supplied natural gas, water and electricity to citizens for free between 1993 and 2017. Turkmenistan experienced high trade deficits from 2015 to 2017 as a result of a subsequent drop in cotton and hydrocarbon prices in 2014, which reduced export sale revenues. Furthermore, the load of foreign debt, along with the persistently low price of hydrocarbons and decline in demand for natural gas purchased by China, together with the pervasive poverty within the country, make the outlook for the economy dismal soon.

Tajikistan is the poorest country among Central Asian countries (World Bank, 2023). The economy is, to a large extent, dependent on remittances, which accounted for about 30% of its total income in 2019. The primary source of income is aluminium and cotton reserves, as well as remittances from migrant workers. However, the country observed high rates of unemployment. For example, the unemployment rate was 15.13% in 2000, 10.24% in 2010 and 7.58% in 2020, respectively (World Bank, 2023).

Kyrgyzstan is an agrarian economy, with primary sector value added (as a percentage of GDP) accounting for 34.18% in 2000, 17.44% in 2010 and 13.57% in 2020. On the other hand, the agricultural sector provided for 53% employment in 2000, 32.24% in 2020, and 19.30% in 2020 out of total employment. The per capita GDP increased from $250 in 2000, $880 in 2010, to $1,180 in 2020 (World Bank, 2023).

The economy of Kazakhstan and Turkmenistan is closely linked with oil wealth. In the case of Kazakhstan, for example, oil rents as a percentage of GDP accounted for 22.87% in 2000, 16.64% in 2010, and 9.33% in 2020. While in the case of Turkmenistan, oil rents as a percentage of GDP accounted for 29.27% in 2000, 14.87% in 2010, and 7.55% in 2019 (World Bank, 2023). At the same time, Kyrgyzstan is found to be an agriculture-based economy.

Such an economic orientation has led to lower growth performance of the stan nations over time. For example, the per capita GDP (current prices) growth rate is found to be a mere 1% in Kazakhstan, 1.12% in Turkmenistan, 1% in Tajikistan, and 1.06% in Kyrgyzstan, respectively, between 2000 and 2020 (World Bank, 2023).

Discussing the connection between economic growth, poverty, and inequality in light of established theory is the fundamental purpose of this study. The rest of the study is as the first section discusses literature review, followed by data source in the second section, methodology in the third section and results and discussion in the fourth section.

Literature Review

Economic Growth and Poverty

A powerful tool for alleviating poverty, which is the root cause of many socio-economic issues, is economic growth. These socio-economic issues include infant mortality, child malnutrition, restricted educational opportunities and the inability to participate in major economic activities. In line with empirical findings, it can be expected that economic expansion can drastically reduce poverty.

By international standards, Central Asia has done remarkably well in economic growth as well as in the reduction of poverty. However, economic expansion might not be a necessary prerequisite for reducing poverty on its own. The available literature suggests that a nation may experience positive economic growth without a trickle-down effect if income inequality rises. Therefore, to evaluate how economic growth affects the reduction of poverty, it is fundamental to analyse income distribution in an economy. This is because the relationship between poverty and growth can be positive or negative depending upon several factors, including income distribution. As mentioned by Perotti (1993), raising income level stimulates the economy to distribute resources across several domains, including healthcare, education and social welfare, so contributing significantly to the reduction of poverty. Similarly, Chen and Ravallion (1996) estimated that a reduction in poverty is associated with a high growth rate in income.

Ravallion (2001) and World Bank (2005) endeavoured to explain the importance of growth in poverty reduction. According to these findings, nations with a higher growth rate tend to experience a lower rate of poverty, whereas those with a low growth rate typically experience a rising rate of poverty. Ravallion (2001) found that if average income rises by 1%, poverty is reduced by 2.4–2.5 percentage points. Moreover, these studies also argue that improved income distribution within a country is conducive to poverty reduction.

Inequality and Poverty

Income inequality is among the burning issues that have been extensively discussed in the economic literature. Discussing the ethical aspect of the subject, such as whether equality is desirable, fair and how much and what kind of equality should be pursued, has constituted a significant portion of this conversation (Sen, 1992). The United Nations Development Programme Report (2007/2008) demonstrates that developing nations have the highest rate of income inequality. Many studies found that countries with a low level of GINI value develop differently from countries with a high level of GINI value. Findings show that wealth inequality affects a country's GDP and poverty rate (Fosu, 2010; Galor & Zeira, 1993). Moreover, many emerging nations in Latin America, Africa and transition zones either worsen poverty and inequality or do little to help the poor (Van der Hoeven, 2014).

Financial Development and Poverty

There are numerous direct microeconomic ties between poverty alleviation and financial development, along with indirect macroeconomic links through economic growth. These connections are made possible if low-income people have easier access to finance, financial tools, services and institutions. Until the late 1980s, work on these microeconomic links was virtually non-existent. It was believed that only through public-sector banks and other institutions—financial development can be beneficial for the overall performance of the economy. Over time, however, it has been found that the private sector is a key player in financial development, enabling poverty reduction across the developing nations. Numerous studies have attempted to probe the link between monetary development, income disparity, poverty and economic growth, including Dollar and Kraay (2002), Honohan (2004) and Odhiambo (2009). The well-known idea is that a country's progress is enhanced by financial development since it allows for the efficient mobilisation of capital, which in turn helps with capital formation and overall development (Levine, 1997). However, these studies do not address the question of whether or not this economic expansion narrows the income disparity between the various social groups and trickles down to the deprived segments of society. Jalilian and Kirkpatrick (2005) investigated the link between rising income and poverty level. For every 1% improvement in financial development, low-income citizens in developing nations would see a 0.4% increase in their income. Beck et al. (2007) find that in nations with a relatively well-developed financial system, the income of the poorest 20% increases at a higher rate than the average GDP per capita. However, Danquah et al. (2017) found that though the development of the financial sector has had a favourable but insignificant impact on the eradication of poverty in case of Ghana. Similarly, Akhter et al. (2010) concluded that although financial market instability is detrimental to the impoverished, financial development aids in poverty alleviation. Odhiambo (2010) asserts that financial development seeks to alleviate poverty through the utilisation of private credit and various financial assets, based on an analysis of the relationship between poverty and financial development in Zambia from 1969 to 2006 using the autoregressive distributed lag (ARDL) technique. In the case of India, Sehrawat and Giri (2016) asserted that financial development and poverty alleviation are cointegrated. The impact of growth in financial sector on poverty alleviation and income inequality reduction in emerging countries was examined by Seven and Coskun (2016). Despite the fact that financial development promotes economic progress, it may not necessarily help the poor in developing nations, according to their findings. They also claimed that stock market and banks do little to help alleviate poverty. Instead, a country's socioeconomic and political context determines the effect of financial development on poverty and inequality reduction.

Inflation and Poverty

Classical economists believe that inflation acts as a tax on income of the poor as it reduces their real income and poses several challenges. For example, higher prices could erode real wages and savings across developing countries, thereby leaving the low- and middle-income households poorer than wealthier households. However, the final impact of inflation on poverty is contingent on the income composition, assets and consumption baskets of households. In all three categories, the inflation elasticity of poverty is high for poor households across the developing countries. A number of studies have found a positive and significant impact of inflation on poverty.

One of the economic issues that practically every nation faces is inflation, which is always discussed in relation to price increases since prices are a key indicator of inflation (Chandra, 2016). Simply put, inflation is the ongoing, generalised increase in prices. A price increase for one or two things alone cannot be considered inflation unless it affects the pricing of other goods and extends to them. The buying power of income decreases due to inflation, particularly for those with modest fixed incomes.

According to empirical findings, poverty is positively impacted by inflation. Talukdar (2012) investigates how inflation affects poverty in developing nations. Poverty and inflation have a positive correlation in lower- and upper-middle-income nations.

Data Source

This study uses time series data from 2000 to 2020, which has been taken from the World Development Indicators and Poverty and Inequality Platform (2021). Poverty reduction is considered a dependent variable, whereas economic growth, financial development, income disparity and inflation are independent variables.

The present study uses consumer spending as a proxy of poverty (PHR) due to its more consistent and reliable recording than income (Danquah et al., 2017; Datt & Ravallion, 1992; Odhiambo, 2009, 2010; Sehrawat & Giri, 2016). It lines up with what the World Bank calls 'the inability to attain minimal standard of living' as determined by basic consumption demands. The present study also uses the Gini coefficient (GINI) to measure income disparity.

Methodology

The available literature has evaluated financial development using a variety of proxy variables, such as wide money, quasi money and domestic credit as a proportion of GDP. Establishing an index as a single proxy for financial development is crucial, given the interconnected nature of these components and the absence of a dedicated metric. The present study utilises the Financial Development Index (FDI), which is a composite of three variables commonly found in empirical studies: (a) private sector domestic credit relative to GDP; (b) broad money stock relative to GDP; (c) gross fixed capital formation as a percentage of GDP. The principal component analysis-based on financial development composite measures, which incorporates the above three parameters, adeptly addresses over-parameterisation and multi-collinearity (Stock & Watson, 2002). To construct the FDI, the following formula has been used:

$$I = \sum_{i=1}^{n} X_i \left(\sum_{j=1}^{n} \left| L_{ij} \right| .E_j \right) / \sum_{i=1}^{n} \left(\sum_{j=1}^{n} \left| L_{ij} \right| .E_j \right) \tag{1}$$

Where the index is represented by I, X_i denotes the i-th Indicator; L_{ij} in Equation (1), represents the factor loading of i-th variable on j-th factor; E_j denotes the eigenvalue of j-th factor.

Jalilian and Kirkpatrick (2005) and Beck et al. (2007) concluded that GDPC is the best measure of economic growth. When the CPI rises by a certain proportion each year, inflation also rises. Low-income people may be more negatively affected by high inflation since they have fewer resources to deal with money problems (Easterly & Fischer, 2001). In line with the availability of data, the present study includes only Kazakhstan, Kyrgyzstan and Tajikistan.

Model Specification

By employing the log-linear specification, impact of financial development, income inequality, inflation, and economic growth on poverty has been explored. Compared to traditional linear requirements, log-linear ones reduce dataset variability and yield more efficient results. The present study made use of the following economic model:

$$LnHCR_t = f(LnGDPC_t, LnGINI_t, LnFDI_t, LnINF_t) \tag{2}$$

The econometric specification of Equation (2) is:

$$LnHCR_t = \alpha_1 + \alpha_2 LnGDPC_t + \alpha_3 LnGINI_T + \alpha_4 LnFDI_t + \alpha_5 LnINF_t + e_t \tag{3}$$

where,

$LnHCR_t$ = log of headcount ratio
$LnGDPC_t$ = log of GDP per capita at period t
$LnGINI_t$ = log of Gini coefficient
$LnFDI_t$ = log of FDI
$LnINF_t$ = log of the rate of inflation
t = time from 2000 to 2020
e_t = error term
a_t = 2 to 5 represents the coefficient of the independent variables

ARDL Approach of Cointegration

Numerous econometric methodologies can be applied to investigate the effect of underlying factors on poverty. Engle and Granger (1987) and Johansen (1991) provided the concept of cointegration tests, which rely heavily on the stationarity of data. The Johansen cointegration test cannot be directly applied when the variables exhibit mixed integration orders of I(0) and I(1) or when any variable is non-stationary. Pesaran et al. (1999, 2001) formulated ARDL methodology to tackle these problems. This methodology surpasses alternative techniques for both mixed-order integration time series and non-stationary time series (Amin et al., 2020). This approach selects optimal lags for independent variables (q lags) and variable of interest (p lags) to clarify data-generating process within a general-to-specific modelling framework. Hence, this technique is more likely to minimise the skewed estimates brought about by concurrent causation between dependent and independent variables. Conventional asymptotic theory underpins the findings and ARDL consistently and credibly estimates the long-run coefficients, even with small samples. Pesaran et al. (1999) state that ARDL approach eliminates serial correlation and endogeneity. However, this model cannot be applied when the dataset is of $I(2)$ order. The specific ARDL model for each nation used in the present study is as follows:

$$\begin{aligned}\Delta LnHCR_t = \alpha_0 + \sum\nolimits_{i=1}^{n} \beta_1 \Delta LnGDPC_{t-i} + \sum\nolimits_{i=1}^{n} \beta_2 \Delta LnGINI_{t-i} + \\ \sum\nolimits_{i=1}^{n} \beta_3 \Delta LnFDI_{t-i} + \sum\nolimits_{i=1}^{n} \beta_4 \Delta LnINF_{t-i} + \lambda_1 \Delta LnGDPC_{t-i} + \\ \lambda_2 \Delta LnGINI_{t-i} + \lambda_3 \Delta LnFDI_{t-i} + \lambda_4 \Delta LnINF_{t-i} + e_t \end{aligned} \tag{4}$$

where Δ is the first difference operator and a_o is a constant. β_i denotes short-run coefficients of model, while λ_{vi} denotes long-run coefficients.

In order to verify if cointegration is present, bounds test compares the variables to null hypothesis H_o: $\lambda_i = 0$ (no cointegration). Coefficient estimates for the test can be obtained from Equation (4). If the variables are cointegrated, the Error-Correcting variant of the ARDL model is to be applied.

$$\begin{aligned}\Delta LnHCR_t = \alpha_0 + \sum_{i=1}^{n} \beta_1 \Delta LnGDPC_{t-i} + \sum_{i=1}^{n} \beta_2 \Delta LnGINI_{t-i} + \\ \sum_{i=1}^{n} \beta_3 \Delta LnFDI_{t-i} + \sum_{i=1}^{n} \beta_4 \Delta LnINF_{t-i} + \theta EC_{t-1} + e_t \end{aligned} \tag{5}$$

Where 'EC' stands error correction term θ is the symbol for adjustment parameter, which is also called speed of adjustment per year. Additionally, occurrence of cointegration among the variables is further supported by negative and significant coefficient of EC term.

Empirical Results and Discussions

To determine the stationarity of a series, ADF test is most commonly used and has been applied in the present study at both levels and first difference. The results are presented in the Table 1 illustrates that the variables included are stationary at both the level and first difference, as indicated by *p* value of respective variables. which validates application of bounds test and ARDL model.

The first step is to apply bounds test to identify long-run relationship among the variables. Table 2 shows the *F*-statistic for long-run coefficients. The Schwartz Bayesian Criterion (SBC) has determined the optimal lag duration for each variable. The value of *F*-statistics confirms long-term relationship among the included variables.

Long-run Results

The majority of the variables show the expected sign and are statistically significant, as presented in Table 3. In cases of Kazakhstan and Tajikistan, impact of GDPC on poverty reduction is negative and statistically significant. The results

Table 1. ADF Levels and First Difference Unit Root Test.

	Kazakhstan		Kyrgyzstan		Tajikistan	
Variable	Level	First Difference	Level	First Difference	Level	First Difference
GDPC	–1.22205	–4.29879	–3.77602	–6.09006	–1.57521	–4.33579
	(0.6435)	(0.0041)	(0.0107)	(0.0001)	(0.4762)	(0.0035)
FDI	–2.06154	–2.91909	–0.66283	–5.95396	–1.15117	–4.90471
	(0.2607)	(0.0617)	(0.8334)	(0.0001)	(0.6738)	(0.0011)
GINI	–1.61741	–7.02957	–1.61777	–6.78433	–2.27309	–4.61085
	(0.4513)	(0.0000)	(0.4536)	(0.0000)	(0.1897)	(0.0030)
INF	–3.77756	–5.76186	–3.88726	–5.5032	–6.10629	–3.12475
	(0.0107)	(0.0002)	(0.0085)	(0.0004)	(0.0002)	(0.0496)
PHR	–2.42152	–5.87891	–3.78254	–3.42987	–2.7731	–3.34819
	(0.1537)	(0.0003)	(0.0111)	(0.0266)	(0.0809)	(0.0323)

Note: Values in parentheses indicate *p* value.

Table 2. Significance of *F*-test for Cointegration.

	Kazakhstan	Kyrgyzstan	Tajikistan			
Model	*F*-statistic	*F*-statistic	*F*-statistic	Significance Level (%)	LCB	UCB
PHRt = *f* (FDIt, PGDPt, GINIt, INFt)	29.117584	4.630824	8.5258564	10	2.2	3.09
				5	2.56	3.49
				1	3.29	4.37

Note: UCB: Upper critical bound values, LCB: Lower critical bound.

Table 3. Results of Long-run Estimates from the ARDL Model (Dependent Variable PHR).

Variable	Kazakhstan	Kyrgyzstan	Tajikistan
LGINI	3.961622***	1.499879***	7.509547**
	[6.170857]	[34.43744]	[2.241985]
LFDI	1.235154***	–2.862652***	–1.014343**
	[5.807488]	[–13.97170]	[–2.175829]
LGDPC	–1.146768***	1.052325**	–0.176210**
	[–10.78844]	[9.037013]	[–2.109544]
LINF	–0.343433***	–0.200256*	0.434691***
	[–4.345264]	[–5.196592]	[2.661546]

Notes: ***, ** and * stands for 1%, 5% and 10% significance level.
The values in the square brackets indicate *t*-statistics.

indicate that 1% increase in GDPC leads to 1.14% and 0.17% reduction in poverty, respectively, in these countries. It is quite acceptable and aligns with findings of Islam (2003), which suggested that higher economic growth could boost employment, productivity, potentially resulting in higher income for the poor. But in the case of Kyrgyzstan, 1% increase in GDPC leads to 1.05% increase in PHR, which is in line with Todaro (1997), who explained that economic growth could either decrease or increase poverty. Similarly, GINI has positive impact on PHR in long run. The results indicate that GINI exerts large influence in Tajikistan and Kazakhstan, with 1% rise in GINI resulting in 7.50% and 3.96% increase in PHR in these countries, respectively. In Kyrgyzstan, 1% rise in the GINI coefficient results in a mere 1.49% increase in PHR. The data indicate that GINI significantly and positively influences PHR, suggesting that inequality exacerbates poverty. These findings align with Fosu (2010), which shows that inequality exerts a direct and positive influence on poverty, with heightened inequality exacerbating poverty levels.

In Kazakhstan, foreign direct investment exerts a substantial and favourable influence on PHR, wherein the poverty rate rises by 1.23% for every 1% increase in FDI. This confirms what Hazari and Mohan (2015) found that low-income groups see their welfare eroded as a consequence of capital accumulation, which leads to lower wages. As Kunieda, Nishimura, and Shibata (2018) show, financial liberalisation can widen wealth gaps around the world. In Kyrgyzstan and Tajikistan, 1% increase in FDI results in a fall of 2.8% and 1.01% in PHR, respectively. It suggests that financial liberalisation substantially influences poverty alleviation. Claessens and Perotti (2007) and Demirgüç-Kunt et al. (2008), among others, have shown that financial access is crucial to alleviating poverty and inequality. Financial instability, according to Jeanneney and Kpodar (2011), makes poverty worse. Inflation has a significant and negative impact in the case of Kazakhstan and Kyrgyzstan, where 1% increase in Inflation leads to 0.34% and 0.20% reductions in poverty. Chaudhry and Chaudhry (2008) have noted a similar direct correlation between poverty and inflation in Pakistan. A decrease in unemployment will be correlated with rising inflation, which could help the poor more than others. Moreover, an increase in inflation lowers the poverty rate, according to Cutler and Katz (1991). Tajikistan shows a positive and significant relationship between INF and PHR, where 1% increase in INF leads to 0.43% increase in PHR. In the case of India, Datt and Ravallion (1992) found that a high inflation rate is associated with high poverty rate. According to Cardoso (1992), poverty is impacted by inflation in two ways: First, rise in inflation may reduce real disposable income. Second, nominal earnings of wage earners rise more slowly than the real costs of commodities they consume.

Short-run Results

Table 4 presents the short-term results that align with long-run results. The findings indicate the positive impact of GINI in Kazakhstan and Tajikistan, while demonstrating a negative impact in Kyrgyzstan. The impact of GDPC on poverty is statistically significant and negative across all nations. The results indicate that 1% increase in GDPC leads to 4.08%, 1.49%, and 0.0017% decrease in PHR for Kazakhstan, Kyrgyzstan and Tajikistan, respectively. FDI exerts a substantial negative influence on PHR. The results indicate that 1% rise in FDI decreases 2.67%, 1.68%, and 0.26% PHR in these nations, respectively.

In addition, there is a significant and negative effect of INF on PHR, as 1% rise in INF results in a fall of 1.6%, 2.6% and 0.34% in PHR. The present study applies specific residual diagnostic procedures to yield robust results, even though the dependence, variance and covariance characteristics of the regression error term may influence these outcomes. We shall now commence diagnostic assessments.

Table 4. Short-run Estimates from ARDL Model (Dependent Variable PHR).

	Kazakhstan	Kyrgyzstan	Tajikistan
	Coefficient	Coefficient	Coefficient
D(LGINI)	3.014379***	–1.104705***	0.913372**
	[13.57453]	[–11.13202]	[2.375892]
D(LGDPC)	–4.088116***	–1.490156***	–0.001780*
	[–22.05245]	[–26.21734]	[–0.532057]
D(LFDI)	–2.672852***	–1.681518***	–0.267148***
	[–11.45926]	[–15.04277]	[–8.485028]
D(LINF)	–0.579157***	–0.086388**	–0.133532***
	[–3.586885]	[–11.42129]	[–10.00983]
CointEq(–1)	–1.686377***	–2.633690***	–0.340758***
	[–19.82643]	[–28.10036]	[–16.82511]
R^2	0.988865	0.997851	0.992115
Adjusted R^2	0.980204	0.993122	0.983245
SE of regression	0.074654	0.020049	0.014890
Durban–Watson test	2.125229	2.728150	2.458933

Note: ***, ** and * stands for 1%, 5% and 10% significance level.

Diagnostic Evaluation and Goodness of Fit

As shown in Table 4, the estimated models have a reasonable level of goodness of fit, as evaluated by adjusted R^2 and the Durbin–Watson test. By demonstrating predictive capabilities of 98%, 99%, and 99%, respectively, estimated ARDL-ECM models demonstrate that they are able to account for about 98% of variation in dependent variable in Kazakhstan, and 99% of variation in Kyrgyzstan and Tajikistan. The Durbin–Watson statistics are 2.1, 2.7 and 2.4, indicating that the models are free of autocorrelation issues.

Figures 2–4 show the result of cumulative sum (CUSUM) and cumulative sum of squares (CUSUMSQ) of recursive residuals obtained from nested subsamples of the data of Kazakhstan, Kyrgyzstan, and Tajikistan, respectively, to assess the stability of short-run and long-run ARDL model. With CUSUM and CUSUMSQ

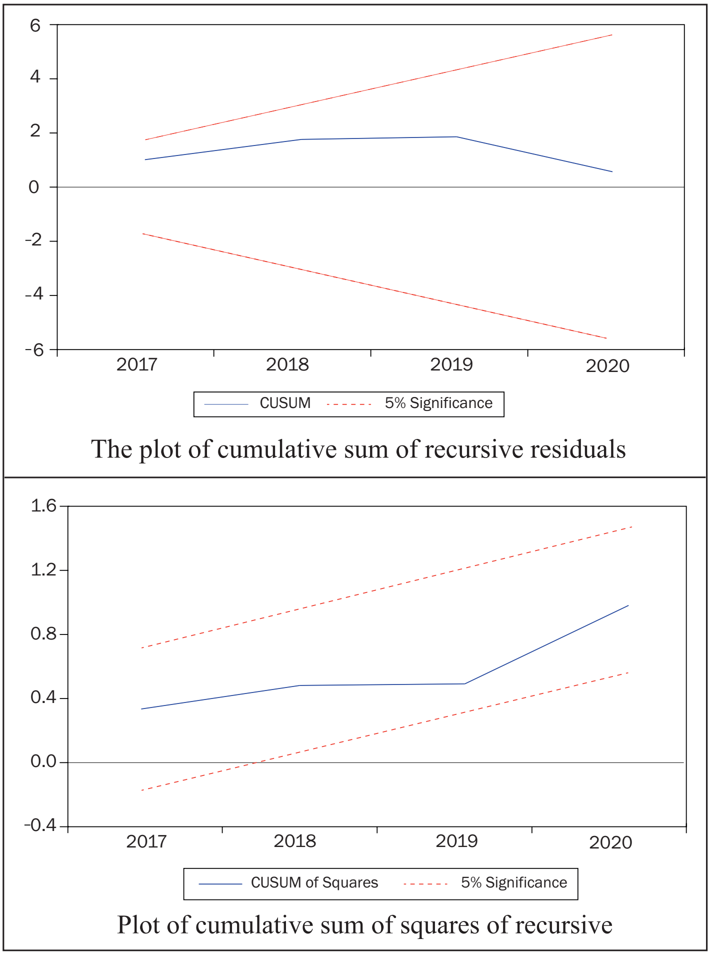

Figure 2. Stability Test of Kazakhstan.

Source: Authors' calculation.

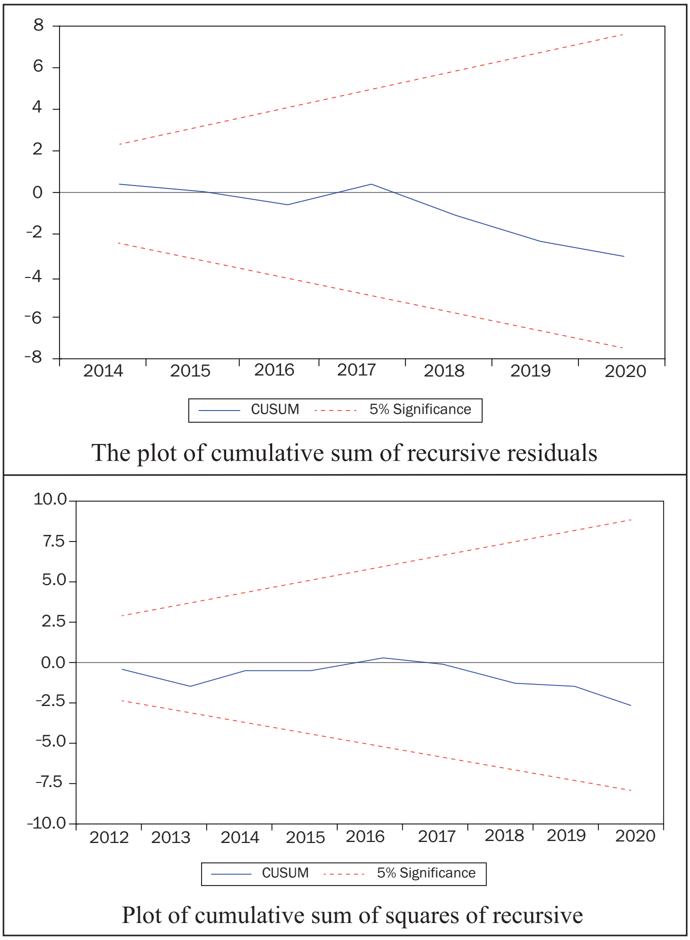

Figure 3. Stability Test of Kyrgyzstan.

Source: Authors' calculation.

values continuously falling below 5% critical thresholds, the figure shows that the ECM coefficient remains constant throughout the sample period. Based on all the evidence, it seems like the models are good for policy analysis because they have good statistical and theoretical properties.

Conclusion

The present study attempted to investigate the poverty-economic relationship in Central Asian countries over 2000–2020. Particularly, it evaluates the impact of economic growth, income inequality, financial development and inflation on poverty levels. The present study applied the time series ARDL estimation

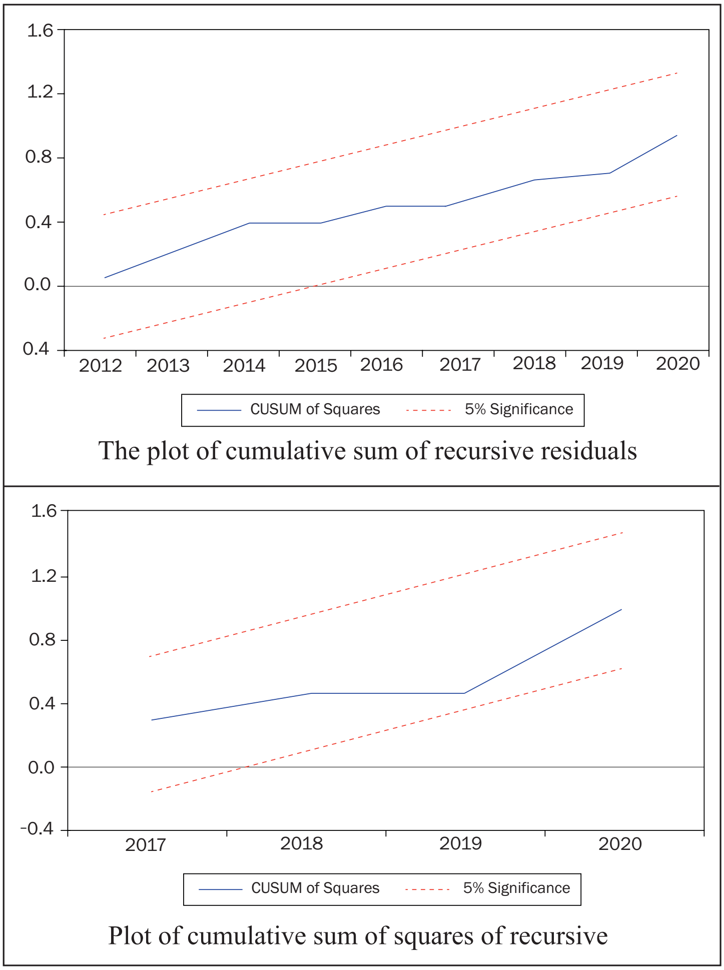

Figure 4. Stability Test of Tajikistan.

technique based on various unit root and cointegration pre-estimation tests. The findings of the study indicate a long-run cointegrating relationship. Economic growth exerts a significant and negative impact on poverty levels, indicating that economic expansion is necessary for poverty reduction. Similarly, income equality has a positive and significant impact on poverty, implying that inequality accentuates poverty levels in all these countries. Further, financial liberalisation significantly reduces poverty levels in Kyrgyzstan and Tajikistan. Inflation has a significant and negative impact in case of Kazakhstan and Kyrgyzstan. Based on these findings, several policy implications can be drawn to address poverty reduction and economic development in Kazakhstan, Kyrgyzstan and Tajikistan:

Promote pro-poor economic growth: Given that economic growth has a significant and negative impact on poverty, it is crucial to prioritise policies that foster economic expansion in all three countries. The Government needs to implement measures aimed at attracting investment, improving infrastructure and supporting entrepreneurship and innovation. This may create employment opportunities, which in turn generate income and may contribute to poverty reduction.

Address income inequality: The positive and significant impact of income equality on poverty suggests that efforts to reduce inequality can contribute to poverty reduction. Policymakers need to implement redistributive measures such as progressive taxation, social protection programs and targeted subsidies to ensure a more equitable distribution of wealth and resources. Investing in education and skills training programs can also help enhance income mobility and reduce income disparities.

Financial liberalisation and access: The present study indicates that financial liberalisation has a positive effect on poverty, particularly in Kyrgyzstan and Tajikistan. Policymakers need to prioritise the development and regulation of inclusive financial systems that promote access to credit, savings and insurance services for the poor and vulnerable populations. This can be achieved by improving financial literacy, expanding microfinance initiatives and fostering competition in financial sector.

Manage inflation: Inflation has been found to have a significant and negative impact on poverty in Kazakhstan and Kyrgyzstan. Therefore, it is crucial to implement effective monetary policies to control inflation rates. Central banks need to focus on maintaining price stability through appropriate interest rate policies, prudent fiscal management and effective regulation of financial sector. Additionally, policymakers need to monitor and address factors contributing to inflation, such as supply-side constraints and external shocks.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship and/or publication of this article.

Funding

The authors received no financial support for the research, authorship and/or publication of this article.

ORCID iD

Suadat Hussain Wani https://orcid.org/0000-0002-7403-8971

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Artificial Intelligence (AI) Versus Human Intelligence (HI): An Analytical Perspective

GLIMS Journal of Management Review and Transformation
4(2) 195–214, 2025

DOI: 10.1177/jmrt.251379963
mrt.greatlakes.edu.in

Diwyanshu Bhange[1], Garima Pratik[1] and Ritesh Dwivedi[1]

Abstract

The revelation of Artificial Intelligence (AI) has been controversial for quite a long time, as most people have questioned whether AI will ever be able to surpass human intelligence (HI). While comparing the details between AI and HI, the abilities and vulnerabilities of each are also outlined in this article. Therefore, systematically, we strive to find accurate overlaps of the Human Mind and Machine Learning in the expanse of Cognitive Psychology, Computer Science, and Philosophy. As for our study, we also make a more pessimistic conclusion, which is a clear difference between human-AI and HI, suggesting that although it has a great ability to perform computing numerical data, pattern recognition, task performance, etc., it cannot generate attributes such as creativity, empathy or a higher-level of context sensitivity. On the other hand, HI has limitations, and they are biologically confined, bias-prone, and subject to bias. However, about the competencies of AI and HI identified in this article, it is argued that the current struggle between those two competitors is a win-win partnership. Thus, by observing each area of responsibility, we can see the benefits we can get from each to achieve the integration that makes it possible for the mutual synergy to ensure the progressive development of the two.

Keywords

AI, artificial intelligence, human intelligence, digital, intelligence, sectors, machine learning, sustainable business

Submitted: 25 May 2025; received 06 July 2025; accepted 21 August 2025

[1] Symbiosis Institute of Business Management, Noida, Symbiosis International (Deemed University), Pune, Maharashtra, India

Corresponding author:
Diwyanshu Bhange, Symbiosis Institute of Business Management, Noida, Symbiosis International (Deemed University), Pune, Maharashtra 412115, India.
E-mail: diwyanshu.bhange2026@sibmnoida.siu.edu.in

Literature Review

The debate regarding whether Artificial intelligence (AI) would soon replace humans has been swelling in the background as technology rapidly advances. Much evidence indicates that although AI performs repetitive, structured work much faster and more precisely than human beings, it still has yet to match the complexity of human creativity, empathy, or judgement. For example, Brynjolfsson and McAfee (2014) contend that AI may replace some jobs, but it also creates opportunities for new types of employment that previously did not exist.

Studies such as those by the World Economic Forum (2020) confirm this, projecting that just like AI will displace some jobs, it will also introduce millions of new ones. These jobs will frequently require abilities such as problem-solving, emotional intelligence (EI), and the capacity to use technology—abilities that machines cannot easily mimic. Scholars such as Bostrom (2014) caution that while AI can analyse information and identify patterns more accurately than humans, it does not 'know' as we do—it has no common sense and moral reasoning.

There is also increasing fascination with how humans and AI can collaborate as opposed to working against one another. Research indicates that companies leveraging AI to aid employees instead of displacing them end up having better outcomes (Davenport & Ronanki, 2018). Nevertheless, most scholars warn that AI will have the same biases as its developers unless closely watched (Jobin et al., 2019). So, while AI is strong, it performs best when it complements human strengths, rather than attempting to imitate or substitute them.

Methodology

To explore this topic in a meaningful way, the research takes a qualitative approach. That means rather than crunching numbers, we are diving deep into existing studies, expert opinions, and real-life examples to understand the bigger picture.

Researching What Is Already Out There

First, we examined current research—books, journal articles, industry reports, and expert studies—dating from roughly the last 10–15 years. This gave us a clear picture of how AI is shaping the job market and what professionals believe about the future.

Finding Patterns in the Information

When we collected all this information, we searched through it for repeated concepts. Are experts concerned about losing their jobs? Is AI being applied sensibly by companies? Are new job opportunities being generated?

Learning from Real-world Examples

We also learned about actual cases from sectors such as healthcare, finance, and marketing—sectors where AI is already being applied. These examples serve to illustrate how AI is being implemented together with humans.

Being Aware of the Limits

This research targets office and professional work more than anything else, so it does not address how AI could impact work in factories or delivery.

Also, since it is grounded in previously published research, it does not involve large-scale surveys or tests.

Introduction

AI is slowly taking over most human jobs, and this research article focuses on the same. Not only this, but it also discusses its future wars as well. Introduction. The 21st century has observed a huge advancement and deployment of AI systems, leading to an extensively debated topic that AI will beat HI. The idea of a battle between AI and HI may sound like the setting for the next Star Wars movie, but it is quickly becoming a reality. Recent events have pushed this issue to the front—with AI systems being able to suddenly demonstrate capabilities that were previously thought to be only in reach of humans.

One such instance from 2020 was Google's AI-powered chatbot Duplex, which reproduced human conversation so well that it fooled many into thinking they were chatting with a robot. The rise of AI-generated deepfakes has raised equal fears around the global application and misuse of AI for fake news and propaganda. Conversely, HI has played a great role in pushing the advancement of AI research, and scientists and engineers are still developing better sorts of retrieved (IR) bases enabled along with deep learning, powered by machine-supplied algorithms doing the most fierce mathematics out there.

AI and HI have huge future employment and educational implications for Miami. With the advancement of AI systems in tasks that once could be performed only by humans, who will need human beings working in an AI-drenched world? Is this going to be AI augmenting human abilities or replacing them? In this article, the author gives a detailed analysis of AI and HI (strengths vs. weaknesses & capacity per se) that ultimately aims to argue against any fear on behalf of HI because the relationship is more symbiotic than fiercely competitive. In doing so, we would gain an even more comprehensive view and perhaps develop a path to move away from it towards coexistence, where both AI and HI empower one another towards greater innovation (Hebb, 1949).

The following words will provide you with a basic understanding of what A. I am, as well as its history and various approaches used to build AI. AI stands for Artificial Intelligence and is defined as the ability of a machine, especially a computer, to mimic the intellectual processes of the human mind. These functions include learning, reasoning, problem-solving, and adaptation. The other type is HI, a natural HI involving emotions, creativity, and learning from experiences. Analysing the differences between AI and HI is essential for predicting the future evolution of AI and its impact on society. The purpose of this article is to demonstrate these forms of intelligence about several criteria to reveal their strengths and weaknesses.

Artificial Intelligence

AI can be described as the simulation of HI in machines that are programmed to understand and learn like humans. These tasks consist of acquiring knowledge, thinking critically, making decisions, perceiving, and comprehending language. AI is a cross-disciplinary science rooted in computer science, mathematics, psychology, neuroscience, and linguistics. Due to technological advancements, AI is widely applied today in areas such as healthcare, finance, transport, and entertainment. The purpose of this article is twofold: first, to explain the definitions and fundamental ideas of AI, and second, to describe its uses in various fields and the general consequences of its advancement (Sternberg, 1985).

Foundational Concepts of AI

Types of AI

AI can be broadly categorised into three types:

1. Narrow AI (weak AI): Smart systems developed to carry out a certain function for a certain period, for example, voice recognition or a game of chess. These highly professional systems lack the flexibility to work on any operation other than the ones they are designed to perform.
2. General AI (strong AI): A theoretical form of AI that is capable of doing everything an intellectual human being is capable of doing. There is no such AI known as general AI to date, and the existing AI models do not possess the ability to do all of these things.
3. Superintelligent AI: A type of AI that is greater than HI in all aspects that one can think of. This is a conjecture, and many discussions among the members of the AI society are held on this issue (Plomin & Deary, 2015).

Machine Learning

Machine learning is a branch of AI that can create algorithms that can train a computer system with a view to making it predict outcomes. There are three main types of machine learning. There are three main types of machine learning:

1. Supervised learning: The algorithm is trained on labelled data; this means that the input that is provided is the correct output. The system then learns how to relate the inputs to the outputs and can predict unseen data.
2. Unsupervised learning: The algorithm is trained from data with no labelled information. It attempts to discover latent patterns or a priori structures in the input data.
3. Reinforcement learning: It learns from an environment through some form of reinforcement in the form of picking up rewards or incurring penalties and, consequently, tries to act in such a manner that it gets the maximum of rewards (Goodfellow et al., 2016).

Neural Networks

Neural networks are one of the core AI technologies derived from the human brain structure and work. Neural networks are networks made up of layers of nodes called neurons that work on data input. Machine learning, specifically neural networks with more than one layer, referred to as multi-layered networks or deep learning, is a major type of AI. Neural networks are especially useful in problem domains such as image recognition, natural language understanding, and others that involve playing games (Mitchell, 1997).

Types of Intelligence

Artificial Intelligence

Logical-mathematical Intelligence.

Logical-mathematical intelligence consists of problem-solving, data analysis, and math reasoning. AI is superior to humans in this area with the help of machine learning algorithms, deep learning patterns, and statistical calculations (Goodfellow et al., 2016). Financial, cybersecurity, and scientific studies use AI to benefit from this type of intelligence in terms of efficiency and precision. AI, however, does not possess a conceptual understanding of the meanings behind calculations, unlike humans.

Machine Learning and Pattern Recognition

AI demonstrates exceptional proficiency in pattern recognition by analysing large datasets and identifying trends (LeCun et al., 2015). This ability underpins AI's effectiveness in fraud detection, predictive analytics, and facial recognition systems. However, AI's pattern recognition is limited by biases in training data and lacks the adaptability that human intuition offers.

Creative Intelligence in AI

Despite historical constraints, AI has also shown creative intelligence with generative models like GPT and DALL-E (Brown et al., 2020). AI-generated art, music, and literature emphasise their capacity to simulate human creativity. Nevertheless, AI is without intrinsic motivation, personal experiences, and emotional depth, which are essential stimulants of human creativity (Boden, 2004).

EI in AI

AI chatbots and virtual assistants deploy natural language processing (NLP) to provide emotional understanding simulating (Poria et al., 2017). Sentiment can be recognised by AI through text and speech, though it lacks emotions and empathy in itself. Goleman (1995) defined human EI as significantly based on experience, social processes, and knowing oneself, attributes that cannot yet be emulated by AI.

Autonomous Decision-making and Ethical Intelligence

Autonomous AI systems, like autonomous vehicles and decision-support software, operate through rule-based decision-making and reinforcement learning (Sutton & Barto, 2018). AI, however, is challenged by ethical decision-making because it depends on predetermined parameters instead of moral intuition (Floridi & Cowls, 2019). HI is responsible for directing AI decision-making to make ethical and socially acceptable decisions.

Human Intelligence

Logical-mathematical Intelligence

Humans have logical-mathematical intelligence, which allows them to break down abstract ideas, identify variable relationships, and use logic to solve complex problems (Gardner, 1983). In contrast to AI, human thinking combines experience, creativity, and intuition with logical reasoning, allowing it to generalise to new situations.

Linguistic Intelligence

Linguistic intelligence entails language understanding, communication, and narrative. Linguistic intelligence is employed by humans to not only exchange information but also comprehend context, humour, and cultural subtleties (Chomsky, 2006). AI models like GPT can produce sensible text but tend to fail at nuanced contextual understanding and cultural awareness.

Emotional and Social Intelligence

Humans have EI, enabling them to understand emotions in themselves and others, build relationships, and achieve social competence (Goleman, 1995). In contrast with AI, human emotions are context-dependent and are determined by personal experiences, hence more adaptive and contextually aware.

Creative Intelligence

Human creativity is a product of imagination, experience, and problem-solving capacity. Humans are capable of producing novel ideas, innovating, and communicating feelings through literature, music, and the arts. Creativity by AI is secondary and does not have the conscious intentionality and meaning that exists in human-made creations (Boden, 2004).

Ethical and Moral Intelligence

Ethical intelligence helps human beings form moral conclusions derived from principles, empathy, and social norms. Although AI systems can be set to obey moral guidelines, AI lack an intuitive sense of morality. Ethical challenges demand deliberation by humans and value-guided decision-making (Floridi & Cowls, 2019).

Applications of AI

Healthcare

AI has completely transformed the healthcare industry through improved diagnostics, personalised treatment planning, and accelerated drug discovery. This goes from AI algorithms studying medical images to developing more accurate diagnoses of cancers at a speed faster than a human radiologist. Similarly, in genomics, it is the AI that identifies the patterns in DNA that could lead to therapies (Ackerman, 1996).

Finance

In the fintech sector, AI is used to identify fraud, automate trading, and manage risks. AI systems can quickly process huge volumes of financial data in real-time, flagging up fraud and even advising on investments through predictive analytics. They also make customer service evolve through chatbots and virtual assistants offering financial advice, with a view to personalised banking data (Roman, 1988).

Transportation

AI is a driving force behind autonomous vehicles, which are expected to transform transportation. Self-driving cars use AI to perceive their environment, make decisions, and navigate safely. AI also optimises logistics and supply chains by predicting demand, optimising routes, and reducing costs.

Entertainment

Netflix and Spotify have custom algorithms to recommend movies or songs based on past preferences, for example. More generally, AIs write content of their own: music, video game levels, film scripts, and the like. AI can adjust to user interactions in real-time and thus deepen the experiences of virtual and augmented reality (Simon, 1956).

Ethical and Societal Implications

Privacy and Surveillance

The most serious threats to personal privacy come from the ubiquitous technology—AI. This much data processing and analytical capabilities will be a curse in spying, surveillance, or snooping. The question remains: where should the line be drawn between our privacy and their AI step?

Bias and Fairness

This is key as AI systems have been known to propagate or, worse, exacerbate the biases in their training data. It can produce biased predictions, especially in high-stakes decisions like hiring, lending, and law enforcement. Fighting bias in AI is an ongoing challenge that demands careful thought at a design level.

Job Displacement

AI is taking over tasks typically carried out by humans, and the fear of job displacement continues to rise. AI may provide new possibilities, but it also puts at risk many positions associated with routine and monotonous activities. Educating and training the workforce can help to alleviate some of this negativity that will come about as a result of such seismic change (Pei et al., 2018).

Overview of HI

Cognitive abilities that allow an individual to perceive information, retain knowledge over time, and utilise the info to solve problems are called HI. It is a multifactorial, polygenic trait and results from complex interactions between genetic predisposition and environmental exposure. HI is not only due to cognitive processes but also emotional and social intelligence, in addition to creativity (Sternberg, 1985).

Characteristics and Dimensions of HI

Cognitive Abilities

HI subsumes a vast array of cognitive functions, such as:

Memory: Storing, retaining, and remembering information. Memory is a key component in learning and problem-solving.

Rationality: The ability to reason, rationalise, and infer from premise to conclusion. This requires deductive as well as inductive reasoning.

Solution-building: It is the capacity to go through complex or new scenarios and find a solution. This needs creativity, a little bit of logical thinking, and the implementation of knowledge.

Learning: The act or process of acquiring knowledge, insight, and behaviour. Human learning is extremely nimble and context-specific (Neisser et al., 1996).

Emotional Intelligence

What is EI? Emotions are complex, unpredictable, and nuanced within the context of human interactions. A person with low EI lacks social interaction and empathy and does not have good communication. EI is a significant element in personal and professional success, being recognised more and more as an essential part of HI (Piaget, 1952).

Creativity

Creativity is the ability to generate new ideas, solutions, or artistic expressions. It involves thinking outside the box, combining existing knowledge in novel ways, and taking risks. Creativity is often seen as a hallmark of HI, distinguishing it from purely cognitive or analytical abilities (Raven, 2000).

Theories of HI

Spearman's General Intelligence (g)

Early in the 20th century, Charles Spearman introduced his theory of general intelligence, or 'g factor' for short. General intelligence is a single underlying factor in performance on diverse cognitive tasks (Spearman). Although people may excel in certain types of tasks, the g factor accounts for a general cognitive ability that undermines all instances of intelligence (Erikson, 1950).

Gardner's Multiple Intelligences

Howard Gardner's theory of multiple intelligences is opposed to universal intelligence. Gardner posited that intelligence is not a single slate but an assortment of eight different intelligences, which are:

1. Image: Linguistic intelligence—The ability to use language effectively.
2. Logical-mathematical intelligence: Reasoning capabilities and problem-solving in mathematics.
3. Bodily-kinaesthetic intelligence: Thinking in three dimensions, recreating or imagining objects and spaces.
   Musical (ability to understand how sounds make music). The ability to use one's own body effectively for physical tasks.
4. Interpersonal intelligence: The ability to understand and effectively deal with others.
5. Intrapersonal intelligence: The capacity to comprehend oneself, which includes one's feelings and motivations.
6. Naturalist intelligence: The ability to identify and classify plants, animals, and minerals.

The theory has had a major influence on the field of education, where it is being implemented in many places around the world. Teaching should be tailored to individual strengths, and intelligence cannot necessarily be measured with traditional IQ tests (Baron-Cohen, 2003).

Sternberg's Triarchic Theory

The triarchic theory of intelligence, formulated by Robert Sternberg, involves three components of human intellect:

1. Analytical intelligence: The capacity to analyse, evaluate, and problem-solve. It is very much old wine in a new bottle as far as traditional academic intelligences are concerned.
2. Creativity: The ability to produce original thoughts and adapt to new circumstances. That means creativity and innovation are part of the equation.
3. Practical intelligence: This is the ability to take what we know and apply it in real life; it's also commonly described as 'street smarts'. Specifically, it relates to abilities in task management and decision-making, as well as adaptability.

Balancing these three types of intelligence is the key to being successful in life, according to Sternberg's theory (Sternberg & Grigorenko, 2002).

Applications of HI

Education

The consequences are too great for educational leadership to remain ignorant about what our research shows concerning not only the generality or distributed Ness of HI but also how much more efficient a multitasking system is than the strictly linear one that most now work within—by which I mainly mean everyone seeks evidence for every point made before accepting it. Gardner thinks educational approaches can be custom-tailored to suit individual learning styles, strengths, and weaknesses when based on his multiple intelligences theory. By accepting and teaching different intelligences, students' scores on assessments will improve, as well as their innovation (Flavell, 1963).

Workplace Performance

At work, human intuition is indispensable for solving problems, making decisions, and inventing. Especially in leadership, teamwork, and customer relations, EI is more and more appreciated. These are the same types of skills that companies now realise they need to illuminate in their pursuit of making progress, and organisations focus on building these competencies with training programmes (Kaufman & Kaufman, 2004).

AI Development

Similarly, research on HI is also guiding the design of AI. The better AI researchers understand how humans think, learn, and solve problems, the more sophisticated machines they will be able to create that are like a human brain. Neural Networks in AI are some of the concepts inspired by how the human brain is structured and functions (Sternberg & Grigorenko, 2002).

Nature Versus Nurture Debate

The nearly century-old debate about the relative roles of genes (nature) and environment (nurture) in HI is alive. The fact that intelligence is largely heritable was deduced from twin studies and analyses of heritability. Fascinatingly, cognitive abilities are strongly mediated by environmental factors—genetics only offers a partial picture of the story.

Emerging research suggests an intricate interplay between nature and nurture, with genes influencing how we respond to our environments and vice versa. This two-way interaction has made the idea that intelligence is not fixed, but developed and purposely created at all stages of our lives (Ceci, 1996).

Influences of Culture and the Environment

Develop, shape, and express intelligence as uniquely human. A culture that values cognitive speed may, therefore, prioritise different forms of intelligence in its schools and encourage the development of other types by their families, rather than one where slowness is revered. These could be verbal and linguistic**.**

For example: The nutritional, educational, and experiential environment can also play a large role in the cognitive development of an individual. Knowledge of these factors and how they might interact with one another sheds new light on disparities in educational and cognitive outcomes between different populations outside the scanner (Plomin & Deary, 2015; Spearman, 1904).

Sustainable Business Management Via AI-HI Alliance

Instead of a rivalry, AI and HI can be a complementary pair when it comes to business management. Sustainable business requires a hybrid mode that taps into the computational powers of AI along with human innovation and ethical sensitivity. Effective integration strategies are as follows:

1. **Human-AI synergy:** Basing AI to handle data-based tasks while allocating decision-making, demanding intuition and experience to humans (Daugherty & Wilson, 2018).
2. **Continuous learning systems:** Creating AI that improves over time through human guidance, promoting ethical and adaptive development (Tegmark, 2017).
3. **Ethical AI governance:** Implementing frameworks to guarantee AI systems are developed in alignment with sustainability and corporate responsibility objectives (Russell & Norvig, 2020).
4. **Education and workforce development:** Companies ought to prioritise reskilling workers to collaborate with AI, promoting long-term viability and job preservation (Brynjolfsson & McAfee, 2017).
5. **Regulatory environments:** Governments and industries need to put in place legal and moral AI usage guidelines to avoid biases and misuse (Russell & Norvig, 2020).

Uses of AI in Business Management

AI has clearly revolutionised business procedures by enhancing efficiency, lowering operational costs, and enabling better decisions based on facts. The major applications are as follows:

1. Automation and efficiency: AI systems perform continuously, making tasks that can be done repeatedly seamless, thereby decreasing human error and maximising productivity (Tegmark, 2017). AI-based automation is giving organisations more opportunities to utilise their resources effectively and eliminate inefficiencies related to manufacturing, customer service, and administration (Huang & Rust, 2018).
2. Predictive analytics: Past data is examined by machine learning algorithms to project future trends of a marketplace or consumer behaviour (Russell & Norvig, 2020). The predictive ability of AI helps companies foresee demand, control inventory, and improve financial planning (Davenport & Ronanki, 2018).
3. Resource optimisation: Environmentally friendly supply chain creations based on AI reduce wastage and optimise logistics, contributing to sustainability aims (Brynjolfsson & McAfee, 2017). AI-based logistics apps facilitate route optimisation planning to save fuel and improve sustainable resource utilisation (Ivanov et al., 2019).
4. Smart decision-making: AI tools provide up-to-the-minute findings to help with strategic position-making or risk evaluation. The massive data processing afforded by AI enables risk assessment and detection of fraud (Makridakis, 2017).
5. AI in customer experience: AI-enabled chatbots and bespoke recommendations motivate customer engagement and satisfaction and, in turn, contribute to better business performance. AI algorithms analyse the behaviour of customers to personalise marketing and enhance retention (Grewal et al., 2020).

The Importance of HI in Business Management

Despite AI capabilities, HI cannot be substituted in situations requiring adaptability, ethics, or complex problem-solving:

1. Creativity and innovation: An area where humans create ideas, innovate in products, and undertake transformation in strategies. Creativity remains the core of product creation, differentiating brands, and entrepreneurship (Amabile, 2018).
2. Ethical judgement: Business decisions, by nature, are often heavily entangled with ethical choices requiring human intuition and moral sense. AI has no moral awareness, so human oversight is therefore inescapable in any ethical business decision-making (Floridi & Cowls, 2019).
3. Emotional intelligence: These rules of leadership, negotiations, and customer relationships are rooted in human empathy and understanding. EI is key in maintaining harmony in the workplace, conflict resolution, and teamwork (Goleman, 2017).
4. Critical thinking: Human thinking permits contextual awareness and the ability to make contextualised decisions beyond the algorithmic capability

of AI. Humans have the capacity to interpret information along with their social, entrepreneurial, economic, and ethical implications (Brynjolfsson & McAfee, 2017).

AI Versus HI

Believed to refer to a computer system being able to mimic human cognitive functions because this is like how humans think, learn, and act. AI Get directly in your inbox. These functions are learning, reasoning, problem-solving, and adaptation. HI is the real/concrete, natural cognitive power of humans, which raises emotional alertness and creativity to be able to learn new situations that come up due to experience.

Comparing AI and HI is key to understanding the long-term trajectory of AI development, as well as its implications for society. The purpose of this article is to compare these types of intelligence based on features grouped around different dimensions, which can provide a perspective into the strengths and weaknesses each has (Herrnstein & Murray, 1994).

Cognitive Capabilities

The Speed and Accuracy of Processing

The power of AI is in processing large volumes of data quickly and accurately. A machine learning algorithm can analyse large datasets, find patterns, and make predictions in seconds, which would take humans much longer. That being said, HI can—in stark contrast to a machine operating with AI capabilities—grapple with context, nuance, and ambiguity, all hurdles that traditional machines have cleared. Predictive analytics is a web on which humans can draw complete or vague conclusions, and AI must be extensively trained to interpret (Hunt, 2010).

Learning Abilities

AI systems, especially those (like ours) that are built on machine learning, get smarter as they see more examples. This conditioning process is data-driven but very narrow; it can seldom generalise outside its specific training scenarios. On the other hand, HI can learn from a greater number of experiences, adapt to new situations, and apply acquired knowledge across contrasting realms. AI is unable to replicate the emotional and social factors at play in human learning (Jensen, 1998).

Decision-making Processes

Logical Reasoning/Intuition

This is because AI works based on logical and statistical analysis to decide what action should be taken. It can decide on pre-set algorithms and accessible data, which is necessary for precision work where humans can be outperformed.

By contrast, HI works in conjunction with a human by considering factors such as intuition. While AI technology can play a key role in larger, more finite systems where the rules of engagement are clearly defined and fixed—as stand-alone units substituting for individual human agency—humans still have an essential differentiability to offer when it comes to making judgements informed by potentially incomplete or missing data (Wechsler, 1944).

Ethical Considerations

AI, by design, lacks the inherent morality and ethics of human decision-making. Although AI can contain ethical guidelines, it does not have the inherent ability to grasp and assess moral dilemmas. Although this task remains difficult, it enables HI to address ethical dilemmas more effectively by improving its understanding of social norms. In the previous section, you just saw a simple example of AI determining if someone should honk or accelerate, but this starts to pose questions about what happens when AI guides decisions that can have moral implications, like autonomous weapons of AI in healthcare (Galton, 1869).

Emotional Intelligence

Recognition and Response

The domain that HI beats AI by a long shot is EI. In other words, humans are capable of detecting emotions in themselves and others, which is a key requirement for normal human social communications. Although AI has made advances in detecting human emotions through facial expressions and tone analysis, these technologies do not consistently demonstrate the same level of empathy as a living person (Goleman, 1995).

Creativity and Innovation

Creativity—This is another big area where true HI can outstrip. It is through emotions, past experiences, and the abstraction of thoughts that humans create outcomes with the help of AI. If we take the concept of creativity, our friend AI can reproduce what creativity looks like, write poetry songs, or even create artwork for us—but it is driven by data and patterns, not original thought. There remains an unmatched potential for innovation among humans today, especially in reaction to any unexpected constraints (Mayer & Salovey, 1997).

Societal and Workforce Implications

AI in the Workforce

Robots replacing some jobs is just the tip of the iceberg when it comes to AI being integrated into work: creating new industries, automating tasks, and improving efficiency, which reduces cost. But this also begs the question of job displacement and what it means for humans in the future workforce. While AI can perform rote work, jobs that rely on EI, creativity, and nuanced decision-making will be less likely to be wholly automated. The combination of AI and HI also creates the opportunity for new joint responsibilities that might require characteristics from both sides (Gardner, 1983).

The following table compares HI versus AI.

Parameter	Human Intelligence	Artificial Intelligence
Evolution	By nature, man has the cognitive abilities to think, reason, and evaluate.	Norbert Wiener is believed to be the first source of ideas for a theory of electronically programmable digital computers with atomic degrees. He exposed these critique mechanisms, and his early contribution was significant in forming today's understanding of AI.
Essence	HI is the product of several cognitive activities that are designed to adjust to new situations.	AI means making computers behave like humans or at least getting them to do things that you would normally have someone else do.
Functionality	Memories, computational abilities, and cognitive skills are what our brains provide.	The operational teeth of AI-powered devices can function because the data connections and commands sent to them tell them what they need.
Pace of operation	They use the memory, processing power, and computational ability they have.	AI-based Device Work—Role of Data and Command Processing.
Learning ability	Humans are slow compared to AI or robots.	Computers store and process information in a way that is faster than humans can do it. But if a general person can solve one calculus problem in five minutes, AI must be able to solve 10 calculus problems in the first minute.
Choice making	Humans can still be swayed by subjective factors outside of numbers.	AI is a headache as a decision mechanism. It makes decisions on all extracted facts, which makes it impartial.
Perfection	There is a very high chance of 'human mistake' when it comes to human insights, meaning that some subtleties can always be forgotten at one point or another.	Since its capacities are built on the basis of a plethora of guidelines that may be edited continually, the ability to provide results exactly is cited here.
Adjustments	It seems that the human mind is very adaptable to new ways of perceiving its surroundings and circumstances. As people can remember things, it not only helps them to enhance their memory but also aids in performing a range of activities.	Unnecessary changes are much more difficult for AI to adapt, and it takes the natural deep learning process longer than we thought.

(Continued)

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Parameter	Human Intelligence	Artificial Intelligence
Flexibility	Juggling several jobs at once is a testament to how important good judgement is when it comes to multitasking.	Just like a framework can only learn the tasks one after the other, AI is the same as carrying out a few fractions simultaneously.
Social networking	No other social animal assimilates hereto-factual knowledge to the degree that we do or has a level of moral self-awareness and sympathetic concern with others akin to ours. It is no wonder: we are social animals.	Also, AI cannot discern real-world social and emotional signals.
Operation	It can be called inventive or creative in a way.	It improves the system's performance. While robots may not be able to think the same way humans do, they definitely cannot produce creative or inventive imagination.

Source: Kumar (2025).

What Will Be the Future of Humans Versus AI?

The potential of AI is ever-expanding. The fact is that AI systems require quite a long time to develop, so they cannot take place without human intervention. HI is a prerequisite to all kinds of AIs, including self-driving cars, robots, computer vision, and NLP (Schneider & Shiffrin, 1977; Thurstone, 1938).

How AI Will Impact Future Jobs

Automation of Tasks

One of the largest impacts to be driven by AI is input from digitalisation and automation, where manual processes in many industries are being replaced or augmented with automated ones. Previously done manually, these tasks are now automated. Tasks or jobs that are repetitive in some form and involve managing vast amounts of data to be communicated with and executed by a computer (often without the computing prowess required in all cases for human intervention) (Floridi, 2016).

New Opportunities

The workforce of the future is presented with novel possibilities by AI, which automates once labour-intensive tasks. Fast technological growth causes fields of study or work to appear where people like digital engineers are needed. Hence, traditional manual jobs may disappear, but new opportunities and professions will be created (Luria, 1966).

Economic Growth Model

Applied properly, not just shoehorned in, AI can make a company way more productive and cooperative by knocking down new walls that could never have been knocked down. This might, in turn, mean greater demand for goods and services, hence driving an economic growth model that shares prosperity, improving the average quality of living for a particular population (Hawkins, 2021; Torrance, 1974).

Role of Work

More than a focus on securing jobs, it is the recognition of employment potential, especially in AI times, that matters more. It speaks to core elements of the human experience, involvement, and creation together for a cause with us, and getting involved in general, and thus should not be forgotten. Even boring and mundane tasks in our jobs are meaningful from time to time, which is why if these tasks get eliminated or automated, they should be replaced with something else that offers us a similar opportunity for human expression (Russell & Norvig, 2016).

Creating New Ideas and Innovation

Now, the experts have enough time to just do a deeper analysis and come up with new, original solutions that are still within human intellect. Agile robots, AI & industrial automation will take care of other simple physical tasks that used to be done by humans (Bostrom, 2014).

Summary (Will AI Replace Humans?)

AI is revolutionising the workplace, introducing a level of unprecedented efficiency and automation to global industries. From analysis of data to predictive modelling, AI's capability to process vast quantities of data at high speeds has made it a business tool of choice to streamline operations and minimise human errors. Yet, though AI excels at executing structured and repetitive tasks with amazing accuracy, it cannot substitute the uniquely human characteristics that fuel innovation, leadership, and creativity.

One of the key points about integrating AI is understanding that it is a complement to, not a substitute for, HI. Although AI can recognise patterns, produce insights, and conduct logical processes at a much greater speed than a human, it is incapable of thinking abstractly, empathising, or making complex moral judgements. Creativity, strategic thought, and human communication are domains where HI excels—attributes that are challenging, if not impossible, for AI to simulate.

The anxiety that AI will bring mass job loss ignores the reality that technological change has always generated new positions and not simply wiped out jobs. Rather than taking away human employees' jobs, AI will likely reformulate work tasks from more repetitive and routine tasks to higher-level, more valuable work. For instance, in medicine, AI can help diagnose illnesses from medical images and data, but doctors' jobs in interpreting scans, interacting with patients, and deciding on the ultimate treatment cannot be replaced. Likewise, in creative arts like marketing and design, AI can assist in ideation and automating content creation, but artistic vision and creativity are still not replicable.

Instead of fighting AI, companies and professionals need to adapt to it as a productivity driver and innovation promoter. The most important thing about surviving in the age of AI is being able to adapt—acquiring competencies that cannot be easily substituted by AI. Critical thinking, problem-solving skills, leadership skills, and EI will become even more desirable as AI becomes responsible for mechanised processes. Companies need to upskill, making sure workers are equipped with the skills and knowledge to better utilise AI.

Simultaneously, ethical standards need to remain paramount in adopting AI. AI-based decisions, though very efficient, need to be controlled through human intervention so that biases do not creep in, fairness can be ensured, and accountability can be maintained. As AI permeates deeper into different sectors of the economy, it is necessary to create policies and regulations that encourage responsible use but avoid unwanted results. AI must be used as a means of augmenting ethical decision-making instead of substituting human judgement for practical and morally complicated situations.

The end goal for AI is not to replace humans but to enable them. Using AI's abilities, we can liberate time and energy to spend on activities involving creativity, instinct, and human interaction. The optimal way is one of partnership—where AI increases productivity, simplifies processes, and allows individuals to achieve their potential. Those organisations that can embed AI in their activities while keeping human skills at the forefront will be more likely to spur innovation, generate new work opportunities, and thrive in an increasingly AI-saturated world.

As we proceed, the question is not if AI will take over human jobs but how it can reframe them for the positive. By using AI as an ally, humans and businesses can explore new frontiers, enhance effectiveness, and maximise what is possible. Rather than dreading the emergence of AI, we should consider it as a chance to heighten human potential, improve problem-solving skills, and bring about a future where humans and machines collaborate to address intricate problems. The real potential of AI is not in displacing HI but in augmenting it, fuelling innovation, and building a smarter and more productive world.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship and/or publication of this article.

Funding

The authors received no financial support for the research, authorship and/or publication of this article.

ORCID iD

Diwyanshu Bhange https://orcid.org/0009-0004-0213-0367

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Assessing the Impact of Digital Transformation on India's FMCG Sector: A Viewpoint

GLIMS Journal of Management Review and Transformation
4(2) 215–226, 2025

DOI: 10.1177/jmrt.251394898
mrt.greatlakes.edu.in

Yudhajit Roy[1] and Kanupriya[1]

Abstract

Digital transformation has impacted the profitability of India's five leading FMCG firms, including Dabur, Hindustan Unilever Limited (HUL), Godrej Consumer Products Limited (GCPL), ITC and Nestlé. The study evaluates how these digital initiatives have improved financial resilience and efficiency, highlighting net cash flow growth, net profit margin, return on capital employed (ROCE), inventory turnover and gross profit margin. Companies that leverage AI, predictive analytics and digital-first strategies drive more profit and are more agile to market shifts. However, the effects differ due to investment, implementation and market positioning. Companies that adopt a data-driven approach have competitive advantages, while those slow to adopt a digital strategy face changing industry dynamics. Long-term digital success requires investment in scalable digital infrastructure, innovation and workforce upskilling. Policymakers should incentivise digital adoption, conduct research and establish rigorous data protection. Future research could focus on tracking digital performance, assessing the impact of sustainability-driven digital strategies and comparing across industries to improve best practices.

Keywords

Digital infrastructure, digital transformation, FMCG sector, innovation, profitability, workforce upskilling

Submitted 24 August 2025; received 16 October 2025; accepted 22 October 2025

[1] Department of Economics, Indian Institute of Foreign Trade (IIFT), New Delhi, India

Corresponding author:
Kanupriya, Department of Economics, Indian Institute of Foreign Trade (IIFT), New Delhi 110016, India.
E-mail: Kanupriya@iift.edu

Introduction

The Fast-Moving Consumer Goods (FMCG) sector stands as one of the four foundational pillars of the Indian economy, ranking as one of its largest contributors. In 2023, its market size reached US$167 billion, with projections indicating a compound annual growth rate (CAGR) of 27.9% from 2021 to 2027, potentially elevating the total to nearly US$615.87 billion. Approximately 65% of the demand originates from urban regions, while rural demand, accounting for over 35%, is expected to increase due to enhanced government spending and improvements in agricultural productivity. This sector encompasses a wide range of products, including food and beverages, personal care items, household goods and healthcare products. Notably, India's food processing market was valued at US$307.2 billion in 2022 and is on track to achieve a CAGR of 9.5%, reaching US$547.3 billion by 2028. Digital transformation plays a crucial role in facilitating growth, reshaping work processes, consumer interactions and supply chain management. With 780 million internet users, India is projected to contribute approximately US$9.92 billion, or 42% of the FMCG sector's total digital expenditure in 2023. The online shopping sector is expanding rapidly, with forecasts suggesting that the Indian e-commerce market will surge from US$83 billion in 2022 to US$185 billion by 2026, and gross merchandise value (GMV) is expected to reach US$350 billion by 2030 (Aditya Birla Capital, 2025; Statista, 2025).

Market projections indicate a robust growth trajectory with a CAGR of 14.9%, leading the industry to an anticipated value of $220 billion by 2025–2026. Traditional FMCG companies are encountering significant competition from Direct to Customer (D2C) unicorns, which are making substantial inroads through *digital-first* strategies. With changing times, e-commerce and digital advertising have emerged as key players. Despite the sector's impressive growth, challenges such as inflation, supply chain disruptions, increasing raw material costs and cybersecurity concerns persist. However, trends like AI-driven demand forecasting, blockchain-enhanced supply chain management and D2C business models present promising growth avenues. Additionally, rising disposable incomes, increased digital adoption and supportive policies are expected to propel India towards becoming a trillion-dollar FMCG industry in the future (Aditya Birla Capital, 2025; Statista, 2025).

The Indian FMCG sector is currently experiencing a digital transformation that is significantly altering the operational strategies of brands in terms of enhancing efficiency, engaging consumers, and penetrating markets to foster a sustainable future. As consumer behaviour shifts towards e-commerce, personalisation and convenience, FMCG companies are increasingly adopting technologies such as artificial intelligence (AI), big data, the Internet of Things (IoT) and automation to streamline their operations in response to this evolving landscape. The traditional pathways through which FMCG products reached consumers have undergone a fundamental change with the rise of e-commerce and the D2C business model. Key drivers of this digital shift include D2C platforms such as Amazon, Flipkart, BigBasket and JioMart. Furthermore, FMCG brands are at the forefront of digital marketing, accounting for 42% of India's digital advertising expenditure. Innovations such as AI-driven demand forecasting, IoT-enabled smart warehouses and blockchain-based inventory management are making supply chains more agile than ever. Companies like Hindustan Unilever, ITC and Nestlé India are leveraging automation in their distribution centres to enhance efficiency and reduce costs. Additionally, consumer interactions are being revolutionised through AI-powered chatbots, voice assistants and augmented/virtual reality, providing seamless product discovery and personalised recommendations (Aditya Birla Capital, 2025; Statista, 2025).

The process of digital transformation is bridging the accessibility gaps in rural India. The adoption of digital payments through mobile wallets and UPI, along with mobile-centric strategies and government-backed PLI initiatives, is essential for driving growth in the FMCG sector within non-metro areas. However, challenges such as high implementation costs, limited digital literacy and cybersecurity threats persist. As smartphone usage increases, urbanisation accelerates, and a digitally inclined consumer base emerges, digital transformation has shifted from being a luxury to a necessity for FMCG companies in India. The key players in India's trillion-dollar FMCG market over the next decade will be those who effectively leverage data analytics, automation and digital-first consumer engagement approaches (Aditya Birla Capital, 2025; Statista, 2025).

This research examines the influence of digital transformation on Key Performance Indicators (KPIs) within India's FMCG sector, particularly in the context of existing challenges. It specifically evaluates the effects of digital adoption on operational efficiencies (including supply chain optimisation, inventory management and cost reduction, among others), profitability (such as revenue growth, return on investment and EBITDA margins), and customer engagement (including the effectiveness of digital marketing, customer loyalty and personalisation). By addressing these factors, the study aims to offer valuable insights to FMCG companies, policymakers and industry stakeholders on how to enhance digital transformation efforts to ensure sustainable business growth.

Digital transformation has become a crucial driver of change within the FMCG sector, including the Indian FMCG sector. However, despite the promise of digital tools and services to enhance operational efficiency and profitability, their impact varies significantly among different companies and market segments. This study aims to address essential gaps in understanding how digital transformation influences industry performance, particularly within India's landscape.

Review of Literature

This segment reviews extant literature on the impact of digital initiatives on businesses, with a focus on the FMCG sector.

As per Zhang et al. (2015), RFID Cuboids are a data warehousing solution that helps manage data from RFID technology, improving supply chain management for businesses. They assist manufacturers in tracking materials and finding efficient delivery routes, reduce retrieval time in warehouses, and offer real-time tracking of logistics. The system uses data cleansing, frequent pattern mining, and a logistics trajectory model to enhance decision-making and optimise inventory management.

Araneda-Fuentes et al. (2015) argue that supply chain coordination is achieved through contracts between suppliers and buyers, who both make capacity decisions influenced by demand uncertainty. In this arrangement, the buyer commits to purchasing an order at a reduced price in return for the supplier's commitment to meet the anticipated demand up to a specified reservation price. The contract includes a penalty for any unused reserved capacity. This model is based on the framework of the newsvendor problem, with the goal of jointly maximising profits while allowing for competitive open market operations from both parties.

Zhong et al. (2015) introduce a novel feature selection technique for text categorisation known as the Discriminative-semi-supervised FreQuent Pattern-based Feature selection (MaFiQ). In this context, a new methodology is selected that integrates Support Vector Machines (SVMs) and semantic correlation metrics, demonstrating superior performance compared to conventional feature selection methods. The strategy of Enhanced Text Classification Accuracy augments document classification by eliminating irrelevant features. Integration of statistical and semantic features utilises word embeddings to improve classification outcomes.

Magni (2015) proposes an alternative method for assessing investments in uncertain conditions, known as the Aggregate Return on Investment (AROI). Traditional methods such as Net Present Value (NPV) and Internal Rate of Return (IRR) reveal several well-documented shortcomings in investment evaluation. AROI was created to overcome these deficiencies, providing a distinct and reliable approach that effectively measures both investment and efficiency types.

Tazvivinga et al. (2015) argue that the application of research necessitates a systematic analysis and management of uncertainties in supply chain operations. The study highlights the significance of data-driven decision-making, automation, predictive analytics, blockchain technology and AI to enhance transparency, agility and operational efficiency within FMCG supply chains. Through semi-structured interviews conducted with 25 senior supply chain professionals in the FMCG sector, the research identifies six key themes that illustrate the connection between digital transformation and supply chain resilience. Data-driven decision-making, supply chain visibility and transparency, enhancing end-to-end tracking via digital tools such as IoT and blockchain, and automation and robotics are some of these themes.

Zhang et al. (2015) argue for the utilisation of real-time, multi-source manufacturing data to develop a dynamic optimisation model for material handling on the shop floor. This model is exemplified through the use of intelligent trolleys that autonomously request transport tasks, which are subsequently assigned based on real-time information. The research highlights the role of auto ID technologies, such as RFID, Bluetooth and Wi-Fi, in improving traceability and operational efficiency within manufacturing processes. A case study demonstrates the system's effectiveness in minimising empty loading ratios and transport distances.

Wang et al. (2015) argue that inventory rationing in multi-class lost sales systems is essential. They advocate for a combination of dynamic and static rationing strategies. These are optimal prior to order release, while a time-varying policy enhances existing approximations during the replenishment lead time. Consequently, they introduce a simplified dynamic rationing (SDR) policy that surpasses the previous model.

Golmohammadi (2015) argue that the application of the Theory of Constraints (TOC) to enhance job-shop scheduling has been extensively researched. This article examines the Drum-Buffer-Rope (DBR) method within a real-world automotive case study to evaluate its effectiveness. The research investigates the impact of TOC's heuristic scheduling principles on master production scheduling (MPS), throughput and resource utilisation in intricate job-shop environments. The authors conduct simulations within a multi-bottleneck framework and suggest modifications to current TOC heuristics for practical implementation.

Sun et al. (2015) argue that through effective load management, Combined Heat and Power (CHP) systems can assist manufacturers in lowering electricity expenses and enhancing sustainability. The authors present a Mixed Integer Nonlinear Programming (MINLP) model designed to optimise the scheduling of manufacturing processes alongside CHP operations in accordance with Time-of-Use (TOU) electricity pricing. The proposed algorithm employs Particle Swarm Optimisation (PSO) to effectively reduce the electricity costs incurred by the electric vehicle operator and the operational expenses of the CHP, while meeting production objectives. A numerical case study validates the effectiveness of the proposed model.

Lu and Liu (2015) examine the impact of a vendor entering an e-commerce channel within a dual-channel distribution system, as opposed to a single-channel distribution system, in a two-echelon supply chain. Their findings indicate that manufacturers do not necessarily benefit from entering e-commerce, especially when the efficiency of the e-channel is low. This situation could be advantageous for physical retailers, as it leads to a decrease in wholesale prices. The prevalence of e-commerce versus traditional channels is contingent upon customer acceptance and the efficiency of the respective channels. By modelling the interactions between manufacturers and retailers, the article employs a game-theoretic approach to create a framework that encourages the investigation of strategic decisions related to pricing and channel management in the context of manufacturer-retailer dynamics.

González-Varona et al. (2020) assert that integrating adaptation and innovation is essential for digital transformation (DT) in small and medium-sized enterprises (SMEs). They critique current maturity models for being unsuitable for SMEs and propose the Organisational Competence for Digital Transformation (OCDT) model, focusing on governance, alignment, culture, technology, and employee capabilities to improve digital competitiveness. The authors emphasise that SMEs must cultivate crucial skills despite limited resources. Furthermore, Tan et al. (2015) recommend that firms leverage analytical infrastructure to maximise innovation by using big data for decision-making. Their case study of an eyeglass manufacturer illustrates that data mining and deduction graphs can enhance supply chain operations and strategic decisions, suggesting that combining big data analytics with structured decision models boosts efficiency and competitiveness.

Fosso Wamba et al. (2019) present a framework for categorising big data research, emphasising its role in enhancing decision-making, business models, and operational efficiency through real-time analytics and automated decision-making. However, the study lacks industry-specific insights, mainly addressing emergency services. Golini and Kalchschmidt (2015) extend their prior work by analysing contingency factors like company size and product complexity using data from the International Manufacturing Strategy Survey (IMSS). They confirm that global sourcing raises inventory levels, although Supply Chain Management Integration (SCMI) mitigates this, especially in larger firms and those with fewer suppliers. Their study's limitations include a need for a Cost-Benefit Analysis of SCMI, a focus limited to manufacturing without addressing services or retail, and a superficial examination of supplier relationship quality.

Additionally, there is mixed evidence of the relationship between digital transformation and corporate performance in terms of different financial indicators. Digital transformation (DM) negatively impacts both Return on Assets (ROA) and Return on Equity (ROE) in the short term. This decline is primarily attributed to substantial investments in Information Technology (IT), which lead to increased costs and lower ROA until the advantages of these investments are fully realised, a process that can take several years. Conversely, DM has a positive long-term effect on Tobin's Q, which measures market value in relation to asset value. This positive influence reflects the market's expectations of future benefits and enhanced performance resulting from digital transformation initiatives (Jardak & Ben Hamad, 2022). In addition, digital transformation initiatives using the likes of AI, automation, and IoT lead to a considerable improvement in operational efficiency that leads to a reduction in costs and an increase in profits (Kamble et al., 2020). It also seeks to affect financial performance, improve total assets, earnings after taxes, and shareholders' funds and has little impact on tax liabilities (Valaskova et al., 2025).

Some of the variables used to construct and understand a Digital Transformation Index by Yue (2024) are asset liability ratio, capital adequacy ratio, ROE and non-performing loan ratio. While the asset liability ratio helps assess the capital structure of banks, the capital adequacy ratio ascertains the risk resistance capabilities of banks, ROE ratio measures the bank's ability to utilise its own capital. It gives returns on shareholders' capital. Non-performing loan ratio measures the risk of bank loans and the size of banks (Yue, 2024).

It is also important to understand the linkages between digital transformation and the ecological performance of companies, given all the emphasis on sustainability in corporate operations. A study by Wang et al. (2022) investigates the association between digital transformation and the environmental performance of companies in China. The study concludes that digital transformation enhances total factor productivity, stimulates green innovation, and strengthens internal governance controls, which collectively lead to a decrease in pollution emissions in firms. Importantly, the research finds that the effects of digital transformation on environmental pollution are more pronounced in state-owned enterprises (SOEs), industries with high pollution levels, and in the more developed eastern regions of China. These insights are particularly valuable for investors and businesses within the Chinese stock markets, as they highlight the significance of digital transformation in advancing corporate social responsibility (CSR). Moreover, the findings are relevant for emerging market economies, offering direction on improving environmental performance through digital initiatives (Wang et al., 2022). Xie et al. (2023) also contend that digital transformation improves enterprises' ecological performance. It also strengthens the positive impact of green technological innovation sharing among like-minded firms, leading to widespread dissemination and adoption of green technology innovation (Xie et al., 2023).

The next section explains the methodology of this study.

Methodology

The objective of this research is to evaluate the FMCG sector where financial and operational information is publicly available, concentrating on India's six major FMCG companies, in order to analyse the impact of digital transformation on profitability. This research assesses publicly available financial and operational information from six leading Indian FMCG firms to examine the effects of digital transformation on their profitability. Key data sources are annual reports and investor presentations (available on company's websites), Earnings calls and transcripts (based on data from Alpha, Moneycontrol and NSE/BSE filings), Financial data (Bloomberg, CMIE Prowess and Capital IQ), industry insights and reports (NASSCOM, FICCI, Deloitte and KPMG); and news articles and expert commentary (ET Retail, Business Standard and Financial Express).

For the purpose of this research, the explanatory variable is the *Digital Transformation Index*. This index includes references to digital transformation in corporate filings, the contribution of e-commerce and direct-to-consumer channels to revenue, disclosed investments in IT, digital transformation and initiatives aimed at digitising the supply chains, such as inventory optimisation and AI-driven demand forecasting. Dependent variables are gross margin (%) (Data from ProwessIQ and MoneyControl), net profit margin (%) (Data from ProwessIQ and MoneyControl), inventory turnover ratio (Data from ProwessIQ and MoneyControl) and capital employed using return on equity (ROCE) (Data from ProwessIQ and MoneyControl). This research employs a combination of descriptive (trends of digital transformation for investments and profitability metrics over time), longitudinal (5-year relationship between digital transformation indicators and profitability metrics), comparative case-based analysis and digital adoption in terms of low versus high for the five companies. Table 1 lists the weights for each metric used in calculating the Digital Transformation Index, along with the reasons for selecting them. So, the Digital Transformation Index comprises the five metrics of Net Cash Flow Growth, Net Profit Margin Change, Inventory Turnover Change, ROCE and Gross Profit Margin Change for the purpose of calculating the composite score by summing up all these components/metrics. The time period for this analysis is 2019–2020 to 2023–2024 (5-year period).

Table 1. Weights Assigned to Each Metric for Calculating the Digital Transformation Index.

Metric	Weight Assigned	Reason
Net cash flow growth	35%	Measures improved operational efficiency due to digitalisation
Net profit margin change	25%	Reflects how digital transformation impacts profitability
Inventory turnover change	15%	Shows supply chain and inventory efficiency improvements
ROCE	20%	Measures how well digital investments improve capital efficiency
Gross profit margin change	5%	Cost savings and price power benefits

These weights are assigned in accordance with their respective significance for a company's financial health on a scale of 100. Robust net cash flows are an indicator of a company's increasing liquid assets, enabling it to cover its obligations, reinvest in businesses, pay its expenses and effectively meet future financial challenges (Hayes, 2025a). The other important variable is the net profit margin change. The same is positive in the case of a company's financial strength and operational efficiency, and is an indicator of its business strategy bearing desired results (Palasciano, 2025). The other important ratio is inventory turnover change, which measures a firm's ability to efficiently sell and replace its inventories using state-of-the-art technologies (including digital tech) (Fernando, 2025). ROCE measures a company's profitability and efficiency in generating profits using its capital (Hayes, 2025b). Last, gross profit margin change indicates the money a company makes from its core operations prior to accounting for its selling, general and administrative costs (Bloomenthal, 2025). As discussed earlier, our Digital Transformation Index comprises the five metrics of Net Cash Flow Growth, Net Profit Margin Change, Inventory Turnover Change, ROCE and Gross Profit Margin Change for the purpose of calculating the composite score by summing up all these components/metrics. The time period for this analysis is 2019–2020 to 2023–2024 (5-year period). The same is being calculated for the five leading companies in India's FMCG landscape that are also pioneers in digital transformation initiatives, ranging from their management to operational processes, as evident from their annual reports.

This study seeks to assess the following. First, measuring the effects of digital transformation on firm profits. Second, determining if firms with larger digital investments have better profit growth. Third, rating companies for their effectiveness in digital transformation. Last, monitoring important trends in the operating ratios of respective firms.

Results and Discussion

Based on Table 2, it could be stated that first, Hindustan Unilever Limited (HUL) is one of the accomplished FMCG firms in India, when it comes to performance. Strong investments in digital supply chain efficiencies, automation and analytics-driven demand forecasting have enhanced its operational performance (+103.7%). Stable Revenue Turnover and Positive ROCE have further contributed to HUL's superior performance. Lower net profit margin of –3.7% in FY24 has been bolstered by the company's elevated capital allocation through its digital transformation initiatives, increasing ROCE to +6.77%. Gross profit margin change stands at –0.68% as immediate gains in profitability are not forthcoming due to the sluggish pace of technology adoption.

Second, Nestlé has seen positive digital-led efficiency improvements as cash flows have increased by 81.9%, indicating that digital investments made in AI-led inventory management, automation and smart supply chain improvements are paying off. Net profit margins have increased by +3.4% and this is a direct result of digital-first initiatives like direct-to-consumer (D2C) strategies and integration with e-commerce. Inventory Turnover has improved by 24% due to digital tools that have optimised the movement of inventory and improved forecasting to reduce inefficiencies. ROCE has grown by +11.1% as digital transformation has produced better ROCE, favouring capital efficiency.

Third, Godrej Consumer Products Limited (GCPL) has seen inventory gains but no concomitant rise in profitability. Inventory turnover is to the tune of +56.2%, thanks to better management of stocks due to AI-driven demand forecasting and automated replenishment. There is also a shrinkage in the bottom line by 64.3%. As digital transformation requires sizeable initial investments in new technologies and processes, immediate gains in profitability may not be forthcoming, as the pace of technology adoption may be sluggish compared to GCPL's peers, leading to slower changes in profit margins and even declining margins. Cash flow grew by 98.3% owing to automation-induced efficiency in working capital.

Fourth, Dabur has witnessed minor movements in its price. Operating cash flows grew 43% owing to gradual gains in operational efficiencies. Net profit margins decreased by –2.02%. Digital investments may not be effective at generating revenues or cost savings on a large scale and, as stated earlier, may involve

Table 2. Comparative Analysis & Scoring of India's Major FMCG Firms.

Rank	Company	Profit Margin Change	Inventory Turnover Change	ROCE Change	Cash Flow Change	Gross Profit Margin Change	Score
1	HUL	–3.7	1.15	6.77	103.7	–0.68	36.8625
2	Nestlé	3.4	24	11.1	81.9	0.45	35.3575
3	GCPL	–64.3	56.2	–16.7	98.3	–2.6	23.29
4	Dabur	–2.02	1.8	–5.69	43	–2.02	13.576
5	ITC	–5.9	–0.27	20.8	16.7	–0.94	8.442

sluggishness in response to digital tech initiatives. Minimal Growth in ROCE at –5.69% is due to less integration with digital transformation.

Last, ITC has seen improvements in ROCE with little growth in cash flows. Due to digital transformation, enabled capital efficiency, ROCE growth increased by 20.8%. However, ITC's cash flow improvements are lower than the industry average at 16.7%, indicating slower financial returns on digital initiatives. Inventory turnover decreased by 0.27%, owing to the possibility of supply chain digitisation not translating into operational efficiencies.

Some notable limitations of this analysis are listed as follows. First, it utilises a limited range of financial metrics, omitting qualitative factors like employee productivity and customer engagement. Second, this study does not specify digital investment breakdowns within firms, complicating ROI assessments. Third, external factors such as regulations and customer behaviour may significantly influence financial performance, in conjunction with digital transformation efforts. Last, the benefits of digital transformation can take time to manifest, with some companies still in early implementation phases, leading to a lag in financial impact.

Conclusion and Future Policy Implications

This study assesses the impact of digital transformation on five major FMCG companies: Dabur, HUL, GCPL, ITC, and Nestlé, focusing on financial metrics like cash flows, profit margins, and inventory turnover. It finds that digital transformation enhances operational efficiency, financial performance, and supply chain optimisation. HUL excels in cash flows and ROCE, leveraging digital capabilities for a competitive edge, while Nestlé demonstrates financial gains through AI and automation. GCPL improved its inventory turnover but faced profitability challenges, suggesting potential improvements in cost structure. Dabur and ITC appear earlier in their digital journeys. Successful transformation requires technology investments aligned with business goals, process re-engineering, and change management. Companies should personalise digital strategies, and policymakers must enhance digital infrastructure, cybersecurity, and workforce reskilling. Additional incentives could encourage SMEs to adopt digital technologies, focusing on sustainable practices, smart logistics, and AI for waste reduction, ensuring long-term competitiveness and resilience.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship and/or publication of this article.

Funding

The authors received no financial support for the research, authorship and/or publication of this article.

ORCID iD

Kanupriya https://orcid.org/0000-0002-4186-4070

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