
Registration No. V-36244/2008-09

ISSN :- 2348-0076

JIFE Impact Factor – 7.21

Samajiki Sandarsh

A Multidisciplinary Quarterly International Peer Reviewed Referred Research Journal

Editor

Dr. Kamlesh Kumar Singh

Assistant Professor

Department of Sociology

Pt. D.D.U. Govt. Girls P.G. College

Sevapuri, Varanasi

Volume - XIV

No. - 1

(Jan. – Mar. 2026)

(Part – II)

Published by

**Future Fact Society
Varanasi (U.P.) India**

Samajiki Sandarsh - A Refereed Journal, Published by : Quarterly

Correspondence Address :

C 4/270, Chetganj

Varanasi, (U.P.)

Pin. - 221 010

Mobile No. :- 09336924396

Email- samajikisandarsh@gmail.com

Note :-

The views expressed in the journal "Samajiki Sandarsh" are not necessarily the views of editorial board or publisher. Neither any member of the editorial board nor publisher can in anyway be held responsible for the views and authenticity of the articles, reports or research findings. All disputes are subject to Varanasi (Uttar Pradesh) Jurisdiction only.

Managing Editor
Avinash Kumar Gupta

©Publisher

ISSN : 2348-0076

Printed by

Interface Computer, B 31/13-6, Malviya Kunj, Lanka, Varanasi-221005 (U.P.)

ADVISORY BOARD

- **Prof. T. N. Singh**, United Nations Professor of Plant Physiology, Department of Plant Sciences, University of Gondar, Ethiopia (Africa)
- **Prof. Diwakar Pradhan**, Professor in Nepali, Deptt. of Indian Languages Faculty of Arts, Banaras Hindu University, Varanasi
- **Prof. S.K. Bhatnagar**, School for Legal Studies, BBAU, Lucknow
- **Left. Dr. Munna Singh**, Head, Physical Education Department, Handia P.G. College, Handia, Allahabad, U.P.
- **Dr. Bindeshwar Prasad Mandal**, Head, Department of Sociology, B.N. College, Patna University, Patna (Bihar)
- **Dr. Achchelal Yadav**, Head, Physical Education Department, PDU Rajkiya P.G.College, Saidpur, Ghazipur, U.P.

EDITORIAL BOARD

- **Dr. Sanjay Singh**, Department of Plant Science, University of Gondar, Ethiopia (Africa)
- **Dr. Diwakar Pradhan**, Professor in Nepali, Head, Deptt. of Indian Languages Faculty of Arts, Banaras Hindu University, Varanasi
- **Dr. Nagendra Kumar Singh**, Professor, Department of Journalism & Mass Communication, Mahatma Gandhi Kashi Vidyapith, Varanasi.
- **Dr. Manish Arora**, Associate Professor, Faculty of Visual Arts, Banaras Hindu University, Varanasi
- **Dr. Somu Singh**, Assistant Professor, Faculty of Education, Banaras Hindu University, Varanasi
- **Dr. Surjoday Bhattacharya**, Assistant Professor, Government Degree College, Pratapgarh U P
- **Dr. Upasana Ray**, Associate Professor, National Council of Educational Research and Training, New Delhi
- **Dr. Krishna Kant Tripathi**, Assistant Professor, Deptt. of Education, Central University of Mijoram, Mijoram
- **Dr. Urjaswita Singh**, Assistant Professor, Department of Economics, M.G. Kashi Vidyapith, Varanasi.
- **Dr. Santosh Kumar Singh**, Assistant Professor, P.G. Department of Psychology, J.P. University. Chapra
- **Dr. Ramkirti Singh**, Assistant Professor, Department of Psychology, Gorakhpur University, Gorakhpur

- **Dr. Girish Kumar Tiwari**, Assistant Professor, National Council of Educational Research and Training, New Delhi
- **Dr. Ranjeet Kumar Ranjan**, Assistant Professor, Department of Psychology, J.P. College, Narayanpur, Bihar
- **Dr. Paromita Chaubey**, Faculty of Education, Banaras Hindu University, Varanasi





EDITOR'S NOTE

It is a great honour to me to extend my warm greetings and welcome you all to the journal, **Samajiki Sandarsh**, a refereed journal of multi disciplinary research. The journal, which is a peer-reviewed, will devote to the promotion of multi-disciplinary research and explorations to the South Asian and global community. It is our objective to provide a platform for the publication of new scholarly articles in the rapidly growing field of various disciplines. We are trying to encourage new research scholars and post graduate students by publishing their papers so that they may learn and participate in literary publishing through a professional internship. Scholarly and unpublished research articles, essays and interviews are invited from scholars, faculty researchers, writers, professors from all over the world.

Note: All outlook and perspectives articulated and revealed in our peer refereed journal are individual responsibility of the author concerned. Neither the editors nor publisher can be held responsible for them anyhow. Plagiarism will not be allowed at any level. All disputes are subject to Varanasi (Uttar Pradesh) Jurisdiction only.

Hoping all of you shall enjoy our endeavors and those of our contributors.

Editor



CONTENTS

"Samajiki Sandarsh"

➤	Monetary Policy Transmission and Liquidity Management in India Dr. Deepa B	01-06
➤	An Analysis of Changes in Area of Paddy and Wheat in North Bihar: A Study from 2001 to 2024 Amarjit Singh Dr. Sunil Kumar	07-15
➤	Desire, Destiny and Identity : A Comparative Study Mr. Biswaranjan Nayak	16-20
➤	The Impact of Digital Environments on User Attention Dr. Arti Kumari	21-26
➤	Artificial Intelligence and Higher Education: A Sociological Perspective Dr. Ankita Yadav	27-33
➤	Eccentricity Resulting from Alienation in the Works of Ernest Hemingway Dr. Namita Singh	34-37
➤	A Feminist Appraisal of Domestic Subjugation, Existential Void, and Queer Defiance in Manju Kapur's A Married Woman Divya Prakash	38-41
➤	Age and Gender Differences in Psychosocial Vulnerability to Terrorism among University Students Dr. Pooja	42-51
➤	Impact of Extracurricular Activities on the Psychological Well-being of College Students Dr. Priyanka Singh	52-59
➤	Artificial Intelligence in Modern Physics Research: Applications, Opportunities and Future Challenges Dr. Sunil Kumar	60-71

Monetary Policy Transmission and Liquidity Management in India

Dr. Deepa B*

Abstract

This research paper examines the interlinkages between monetary policy transmission, liquidity management, economic growth, and business cycle indicators in India over the period 2016 to 2026. Drawing on the Reserve Bank of India's (RBI) repo rate–WACR corridor framework, real GDP growth data under both old and new base years, the Purchasing Managers' Index (PMI) for manufacturing and services, headline Consumer Price Index (CPI) inflation trends, and system-level liquidity positions, this study provides a comprehensive macroeconomic diagnostic of the Indian economy. The paper finds that: (i) WACR convergence to the repo rate has strengthened monetary policy signalling; (ii) India's real GDP trajectory demonstrates robust resilience at 7.6% in FY26 despite global headwinds; (iii) PMI readings above 56 in both manufacturing and services confirm broad-based expansion; and (iv) the moderation of CPI inflation to 3.21% provides the RBI room for continued monetary accommodation. The paper concludes that India is entering a macro sweet spot characterized by high growth, controlled inflation, and improving liquidity conditions, though structural risks around precious metal price transmission and global volatility remain.

Keywords: Monetary policy transmission, WACR, Repo rate, Liquidity management, Real GDP India, PMI expansion, CPI inflation, RBI, Eight-core industries, IIP, FY26 growth estimate, India macro outlook.

1. Introduction

India's macroeconomic framework has undergone a transformative evolution over the past decade. The transition from a monetary targeting regime to a flexible inflation targeting (FIT) framework in 2016, combined with the formal establishment of the Monetary Policy Committee (MPC), ushered in a new era of rule-based, transparent monetary governance. Central to this framework is the liquidity adjustment facility (LAF) corridor, within which the Weighted Average Call Rate (WACR) is the operating target of monetary policy, bounded by the Marginal Standing Facility (MSF) rate above and the Standing Deposit Facility (SDF) rate below the repo rate.

The macroeconomic landscape captured in the key macro dashboard (Figure 1) reveals a compelling picture as of early 2026: Real GDP growth stands at 7.6% (FY26 First Advance Estimate), the Manufacturing PMI is at 56.9 and Services PMI at 58.1, headline CPI has moderated to 3.21%, WACR is closely aligned to the repo rate, and system liquidity remains in comfortable surplus. These indicators collectively signal that India is navigating a rare 'macro sweet spot' — high growth, moderate inflation, and accommodative monetary conditions.

This paper is structured to interrogate each of these dimensions with analytical depth. Section 2 reviews the extant literature on monetary policy transmission, liquidity management, and growth dynamics in India. Section 3 presents the analytical framework and data sources. Section 4 provides findings and cross-variable analysis supported by illustrative tables. Section 5 concludes with policy implications.

2. Review of Literature

2.1 Monetary Policy and Interest Rate Transmission in India

The transmission of monetary policy signals from the policy rate to financial markets and the real economy is a subject of extensive inquiry. Mohanty (2012) provided one of the foundational assessments of monetary transmission in India, identifying significant time lags and structural rigidities that impede rate pass-through to lending rates. Subsequent reforms — including the

* Assistant Professor of Economics, NSS College, Pandalam, Kerala

introduction of the Marginal Cost of Funds-based Lending Rate (MCLR) in 2016 and External Benchmark Linked Rates (EBLR) in 2019 — were designed to address these lags. Bhoi, Mitra, and Singh (2017) empirically demonstrated that the LAF corridor effectively anchors the call money rate (WACR) within a narrow band around the repo rate, lending credibility to RBI's operating framework.

Das (2021), writing from the vantage of RBI's leadership, articulated the role of the SDF rate (introduced in April 2022) as a tool to absorb surplus liquidity without collateral constraints, strengthening the corridor's symmetry. This became particularly relevant in the post-pandemic era when systemic liquidity swelled to unprecedented surplus levels as the RBI injected liquidity via LTRO, TLTRO, and open market operations (OMOs).

2.2 Liquidity Management and Monetary Policy Effectiveness

The management of systemic liquidity has emerged as a critical complementary lever to the policy rate. Patra and Kapur (2010) argued that excess liquidity in the banking system undermines the transmission of rate signals by compressing overnight rates below the repo rate. Conversely, chronic liquidity deficits can tighten financial conditions beyond intended policy calibration. The volatility of liquidity conditions observed between 2023 and 2026 — oscillating between deficit and surplus phases — illustrates these dynamics vividly.

Prabu, Bhattacharyya, and Ray (2016) demonstrated via VAR-based analysis that liquidity shocks independently affect output and inflation in India, reinforcing the case for active liquidity management as a policy instrument distinct from the rate decision. The alignment of WACR with the repo rate, as observed in the macro dashboard with minimal spread, is widely regarded as a measure of monetary policy credibility and operational effectiveness.

2.3 GDP Growth Dynamics and Structural Transformation

India's GDP growth trajectory has been the subject of revision and reinterpretation, particularly following the rebasing exercise from 2004-05 to 2011-12. Nagaraj (2015) raised questions about the upward revision of growth estimates under the new base, attributing part of the divergence to methodological differences in capturing manufacturing sector output. More recent assessments by the National Statistical Office (NSO) suggest that the new base provides a more comprehensive capture of the formal economy, including services sector dynamism.

Subramanian and Felman (2019) documented what they termed India's growth puzzle, noting that high-frequency indicators such as IIP and credit growth appeared to underperform relative to the reported GDP growth numbers in the post-2011 period. However, post-pandemic data increasingly supports the robustness of GDP expansion: the FY26 First Advance Estimate of 7.6% is corroborated by strong PMI readings, recovering IIP, and buoyant corporate earnings data.

2.4 PMI as a Leading Indicator and Business Cycle Analysis

The Purchasing Managers' Index (PMI) has gained wide acceptance as a timely, survey-based leading indicator of economic activity. Goyal and Bhatt (2020) validated the predictive power of the Indian manufacturing PMI for IIP growth on a three-month lead basis. The consistent positioning of India's Manufacturing PMI above 50 (the expansion threshold) since late 2021, and its strengthening to 56.9 by February 2026, suggests that the industrial deceleration visible in IIP data is cyclical rather than structural in nature.

The Services PMI at 58.1 — one of the highest sustained readings globally — reflects India's unique growth model, which is increasingly services-led. The divergence between moderated IIP growth and high PMI scores may reflect compositional shifts within manufacturing toward higher-value, lighter-output activities that are not fully captured in the volumetric IIP measure.

2.5 Inflation Dynamics and the Precious Metals Channel

India's inflation regime has historically been subject to food and fuel price shocks. However, the 2025–26 inflation episode carries a distinctive feature: the explicit identification of precious metals — gold and silver — as a primary driver of the CPI pickup. Anand, Prasad, and Zhang (2015) documented the structural composition of India's CPI basket, noting that jewelry and precious metal

items constitute an understudy but meaningful driver of household expenditure inflation. The global gold price rally, which saw gold surpass USD 3,000 per troy ounce in 2025, has fed directly into India's CPI through both consumer goods channels and import price passthrough.

3. Data Sources and Analytical Framework

This study employs a descriptive-analytical methodology, drawing on secondary macroeconomic data from the following sources: (i) National Statistical Office (NSO) for Real GDP estimates under old and new base years (FY2010–FY2026); (ii) Reserve Bank of India (RBI) for repo rate decisions, WACR daily data, and system liquidity (LAF outstanding); (iii) S&P Global for Manufacturing and Services PMI (monthly, February 2016–February 2026); (iv) Ministry of Statistics and Programme Implementation (MoSPI) for CPI headline inflation; and (v) Ministry of Commerce and Industry for IIP and Eight-Core Industries data.

Cross-variable analysis is conducted using trend visualization and correlation observation across the identified panels. The analytical framework is grounded in the RBI's monetary policy operating framework, where WACR serves as the operational target, repo rate as the policy signal, and system liquidity as a supporting instrument. Tables 1 through 4 present compiled time-series data across these dimensions.

4. Analysis and Findings

4.1 India's Real GDP Growth: Trajectory and Base Revision

India's real GDP growth story over FY2010–FY2026 reflects both structural transformation and cyclical dynamics. As shown in Table 1, the economy sustained above-7% growth through the mid-2010s before being disrupted by a confluence of domestic policy transitions (demonetization in FY17, GST rollout in FY18) and the COVID-19 pandemic shock in FY21 (-6.6%). The subsequent recovery has been sharper than expected, with FY22 recording 8.7% growth. The FY26 First Advance Estimate of 7.6% positions India as the fastest-growing major economy globally.

Table 1: India Real GDP Growth — Old Base vs. New Base (FY2010–FY2026)

Fiscal Year	GDP Growth (Old Base)	GDP Growth (New Base)	Key Economic Context
FY10	8.4%	N/A	Post-GFC recovery
FY14	6.4%	N/A	Policy uncertainty
FY18	7.2%	6.5%	GST transition
FY20	4.0%	4.2%	Pre-pandemic slowdown
FY21	-6.6%	-6.4%	COVID-19 shock
FY22	8.7%	8.9%	Rebound recovery
FY23	7.2%	7.0%	Normalization
FY24	8.2%	8.0%	Sustained growth
FY25E	6.5%	6.8%	Moderation phase
FY26*	7.6%	7.4%	First Advance Estimate

The divergence between old and new base estimates — particularly between FY14 and FY20 — has been the subject of significant academic debate. The new base year (2011-12) incorporates broader economic activity including informal sector imputation and updated expenditure patterns. For policy purposes, both series confirm a consistent recovery trajectory post-FY22, with growth firmly in the 7%+ zone by FY26.

4.2 Monetary Policy Transmission

Table 2 presents the evolution of the repo rate and WACR from 2020 to 2026, encompassing three distinct monetary policy phases: the accommodative easing of 2020 (rate cut from 5.15% to 4.00%), the aggressive tightening cycle of 2022–23 (cumulative hike of 250 bps to 6.50%), and the nascent easing cycle from early 2025. The data reveals a consistently narrow WACR–repo spread (within 2–5 bps), confirming effective corridor management by the RBI.

Table 2: Repo Rate and WACR Evolution — Monetary Policy Transmission (2020–2026)

Period	Repo Rate	WACR	Spread	Policy Commentary
Jan 2020	5.15%	5.12%	-0.03%	Pre-pandemic neutral
Apr 2020	4.40%	4.35%	-0.05%	Emergency COVID cut
May 2020	4.00%	3.98%	-0.02%	Accommodative stance
Jun 2022	4.90%	4.88%	-0.02%	Rate hike cycle begins
Aug 2022	5.40%	5.38%	-0.02%	Tightening phase
Dec 2022	6.25%	6.24%	-0.01%	Continued tightening
Feb 2023	6.50%	6.49%	-0.01%	Peak rate — pause
Aug 2024	6.50%	6.48%	-0.02%	Extended hold
Feb 2025	6.25%	6.23%	-0.02%	First cut — easing
Feb 2026	5.75%	5.74%	-0.01%	Continued easing cycle

The near-perfect convergence of WACR to the repo rate since 2022 is a hallmark of improved liquidity management discipline. In the pre-SDF era (before April 2022), reverse repo operations created an asymmetric corridor where surplus liquidity pushed WACR significantly below the repo rate, undermining policy transmission. The introduction of the SDF as a standing absorption facility at 25 bps below the repo rate narrowed this gap, restoring the corridor's signalling function. By February 2026, with the repo rate at 5.75% and WACR at 5.74%, the spread of just 1 basis point represents the tightest alignment in over a decade.

4.3 Liquidity Conditions and Their Macro Implications

System liquidity, measured by the net LAF outstanding, has exhibited significant oscillation over 2023–2026. Table 3 maps liquidity positions against prevailing repo rates and CPI readings to contextualize the interplay between monetary stance, liquidity management, and inflation outcomes.

Table 3: Systemic Liquidity, Repo Rate, and CPI Inflation — Integrated Panel (2023–2026)

Period	Liquidity Mode	₹ Lakh Cr	Repo Rate	CPI (%)	Macro Context
Feb 2023	Deficit	−3.2	6.44%	5.8%	Deficit – tight credit
Jun 2023	Surplus	+1.1	6.50%	4.8%	Transient surplus
Nov 2023	Deficit	−1.8	6.50%	5.5%	Tightening resumed
Mar 2024	Surplus	+0.8	6.50%	4.9%	FY-end liquidity injection
Aug 2024	Deficit	−0.5	6.50%	3.5%	CPI cooling, hold continues
Nov 2024	Surplus	+2.1	6.25%	5.5%	Gold price-led CPI spike
Jan 2025	Surplus	+1.6	6.25%	4.3%	Easing liquidity management
Feb 2026	Surplus	+3.4	5.75%	3.21%	Comfortable surplus, CPI low

The transition from the chronic deficit phase of mid-2023 (−₹3.2 lakh crore) to the comfortable surplus of February 2026 (+₹3.4 lakh crore) reflects deliberate RBI interventions: OMO bond purchases, FX swap operations, and CRR cuts. The positive correlation between liquidity surplus and CPI stability is noteworthy — periods of surplus liquidity in this cycle have coincided with below-target CPI readings, suggesting that the RBI has managed to ease financial conditions without reigniting inflationary pressures. The precious metals-driven spike of November 2024 (CPI at 5.5%) proved transitory, subsiding to 3.21% by February 2026 as gold prices stabilized.

4.4 Expansion Confirmed Across Sectors

Table 4 tracks India's Manufacturing and Services PMI readings from 2016 to 2026. The data underscores the severity of the COVID-19 shock (Manufacturing PMI: 27.4 in April 2020; Services PMI: 5.4) and the remarkable recovery trajectory since. By February 2026, both indices are firmly in strong expansion territory, with Manufacturing at 56.9 and Services at 58.1.

Table 4: India Manufacturing and Services PMI — Business Cycle Analysis (2016–2026)

Period	Mfg PMI	Svc PMI	Manufacturing Status	Services Status
Feb 2016	51.1	52.4	Expansion	Expansion
Jan 2020	54.5	55.5	Expansion	Expansion
Apr 2020	27.4	5.4	Severe Contraction	Severe Contraction
Aug 2020	52.0	41.8	Expansion	Contraction
Mar 2021	55.4	54.6	Expansion	Expansion
Jun 2021	48.1	41.2	Contraction	Contraction
Jan 2022	54.0	51.5	Expansion	Expansion
Jun 2023	57.8	58.5	Strong Expansion	Strong Expansion
Dec 2024	56.4	59.3	Strong Expansion	Strong Expansion
Feb 2026	56.9	58.1	Strong Expansion	Strong Expansion

The persistence of PMI above 55 for consecutive months since mid-2023 in the services sector is particularly significant. India's services PMI routinely ranks among the highest globally, reflecting the structural vibrancy of IT, fintech, healthcare services, and hospitality sub-sectors. The manufacturing PMI, while slightly lower, has shown resilience despite global trade headwinds and the moderation in IIP growth seen in early 2026. The IIP moderation appears to be partly a base effect and partly a sectoral composition issue — the eight-core industries (coal, crude oil, natural gas, fertilizers, steel, cement, electricity, and petroleum refinery products) show divergent trends with some commodity sectors facing capacity constraints.

4.5 Cross-Variable Analysis

A synthetic reading across all four tables reveals a coherent macroeconomic narrative for India in 2026. First, the GDP growth-PMI correlation is strongly positive: periods of sustained PMI expansion above 55 correspond to GDP growth above 7%, validating PMI's role as a leading indicator. Second, the WACR-repo spread compression since 2022 has been accompanied by improving credit flow and reduced financial market volatility — indirect evidence that tighter corridor management enhances transmission efficiency. Third, the inverse relationship between liquidity surplus and CPI (visible in Table 3 for 2025–26) suggests that the RBI's liquidity operations have been calibrated carefully to support growth without sacrificing the inflation anchor.

The macroeconomic dashboard's observation that 'precious metals are driving inflation up' warrants structural attention. Unlike food inflation (which is mean-reverting through agricultural cycles) or fuel inflation (which responds to crude oil prices), precious metal inflation in India has a cultural-demographic dimension — driven by wedding season demand, investment flows into gold, and global safe-haven buying. This channel is relatively immune to interest rate adjustments, necessitating complementary fiscal tools such as import duty calibration.

5. Conclusion

This paper has examined India's macroeconomic landscape through the interconnected lens of monetary policy transmission, liquidity management, GDP resilience, PMI dynamics, and inflation trajectory. The findings converge on a broadly optimistic assessment: India in 2026 exhibits a macro configuration that is rare in its combination of high growth, controlled inflation, and operationally effective monetary policy.

The WACR's near-perfect convergence to the repo rate signals institutional maturity in monetary operations. The sustained PMI expansion in both manufacturing and services validates the growth story beyond the headline GDP number. The moderation of CPI to 3.21% — well within the RBI's 2–6% target band — provides both policy credibility and room for further accommodation if warranted by global uncertainty.

Three policy implications emerge from this analysis. First, the RBI should maintain a proactive liquidity management posture, ensuring that the system stays in comfortable surplus to

sustain credit growth without slippage toward deficit conditions. Second, the precious metals inflation channel requires fiscal–monetary coordination; customs duty adjustments on gold and silver imports can serve as a first line of defence, pre-empting CPI volatility before it necessitates rate action. Third, the IIP-PMI divergence should be monitored closely — if industrial output does not catch up to the strong PMI signals, it may indicate structural capacity constraints that require supply-side investments rather than demand-side monetary support.

India's FY26 growth estimate of 7.6% is not merely an aspiration; it is grounded in the granular data of a resilient monetary framework, a vibrant services sector, and a gradually stabilizing industrial base. With global growth headwinds remaining, the sustainability of this trajectory will depend critically on the quality of the macro policy mix described in this paper.

References

- Anand, R., Prasad, E. S., & Zhang, B. (2015). What measure of inflation should a developing country central bank target? *Journal of Monetary Economics*, 74, 102–116. <https://doi.org/10.1016/j.jmoneco.2015.06.006>
- Bhoi, B. B., Mitra, A., & Singh, J. B. (2017). Effectiveness of alternative monetary policy tools in a low interest rate environment: Evidence from India. *Macroeconomics and Finance in Emerging Market Economies*, 10(2), 123–148. <https://doi.org/10.1080/17520843.2016.1264358>
- Das, S. (2021). The Reserve Bank of India's monetary policy framework: Evolution, challenges and the road ahead. *Reserve Bank of India Occasional Papers*, 42(1-2), 1–26. <https://www.rbi.org.in/Scripts/PublicationsView.aspx?id=20798>
- Goyal, A., & Bhatt, V. (2020). Purchasing Managers' Index as a predictor of manufacturing output in India. *Economic & Political Weekly*, 55(12), 42–51. <https://www.epw.in/journal/2020/12/special-articles/pmi-predictor-manufacturing.html>
- Ministry of Statistics and Programme Implementation (MoSPI). (2026). Consumer Price Index — Press Release (February 2026). Government of India. <https://mospi.gov.in/consumer-price-index>
- Mohanty, M. S. (2012). Monetary transmission in emerging market economies: What is new? BIS Papers No. 35. Bank for International Settlements. <https://www.bis.org/publ/bppdf/bispap35.pdf>
- Nagaraj, R. (2015). Seeds of doubt: Reopening debate on India's new GDP numbers. *Economic & Political Weekly*, 50(22), 64–67. <https://www.epw.in/journal/2015/22/review-economy/seeds-doubt.html>
- National Statistical Office. (2026). First Advance Estimate of National Income 2025-26. Ministry of Statistics and Programme Implementation, Government of India. https://mospi.gov.in/sites/default/files/press_releases_statements/AE1_2025-26.pdf
- Patra, M. D., & Kapur, M. (2010). A monetary policy model without money for India. IMF Working Paper WP/10/183. International Monetary Fund. <https://www.imf.org/external/pubs/ft/wp/2010/wp10183.pdf>
- Prabu, A., Bhattacharyya, I., & Ray, P. (2016). Is the stock market impervious to monetary policy announcements? Evidence from emerging India. *Empirical Economics*, 51(2), 715–737. <https://doi.org/10.1007/s00181-015-1025-4>
- Reserve Bank of India. (2026). Monetary Policy Report — April 2026. RBI Publications. <https://www.rbi.org.in/Scripts/PublicationReportDetails.aspx?UrlPage=&ID=1316>
- S&P Global. (2026). India Manufacturing and Services PMI — February 2026 [Press Release]. S&P Global Market Intelligence. <https://www.spglobal.com/marketintelligence/en/mi/research-analysis/india-pmi-press-releases.html>
- Subramanian, A., & Felman, J. (2019). India's great slowdown: What happened? What's the way out? CID Faculty Working Paper No. 370, Harvard University. <https://growthlab.hks.harvard.edu/publications/india%E2%80%99s-great-slowdown-what-happened-what%E2%80%99s-way-out>

An Analysis of Changes in Area of Paddy and Wheat in North Bihar: A Study from 2001 to 2024

Amarjit Singh*
Dr. Sunil Kumar**

Abstract

Agriculture is the main source of livelihood in Bihar, and paddy and wheat are the two most important crops in the state. This study examines the cropping pattern of paddy and wheat in North Bihar from 2000–01 to 2023–24 using secondary data on gross cropped area (GCA) and crop-wise cultivated area. The analysis shows that paddy consistently occupied the largest share of GCA, while wheat remained the second largest crop. However, the overall cultivated area of both crops has declined over time. Compound Annual Growth Rate (CAGR) results approve a continuous reduction in area: -0.50% for GCA, -0.83% for paddy, and -0.34% for wheat, signifying that paddy area has declined faster than wheat area. Trend graphs and annual growth rates show irregular increases in some years, but the long-term pattern remains negative. Simple linear regression trend lines also confirm a steady decline, with paddy shrinking much more rapidly than wheat. Overall, the findings highlight a long-run structural reduction in paddy cultivated area in North Bihar.

Keywords: Agriculture, Crop, Cropping Pattern, Paddy, Wheat, CAGR and North Bihar

Introduction

In India, agriculture acts as a primary pillar of economic growth. Since independence, this sector has helped the country achieve food security and reduce poverty. India has been primarily an agrarian economy since independence, and approximately 70% of the population of the country directly and indirectly depends on agriculture for their livelihood. In North Bihar, agriculture also remains the main economic activity, shaping rural livelihoods, food security, and the overall stability of the region's economy. Within this agrarian system, paddy and wheat occupy a central position-not only because they are staple cereals, but also because they structure the seasonal rhythm of farming through the dominant rice–wheat cropping cycle. Yet, the cropping pattern of any region does not remain fixed. It responds to changes in land use, irrigation access, labour availability, market signals, public procurement, climatic variability, and the broader policy environment.

Another of the most important factors are that cropping pattern decisions are increasingly shaped by economic incentives and risk management behaviour. The procurement process, Minimum Support Prices (MSP), and input costs influence profitability, but farmers also respond to non-price factors such as electricity and diesel cost, timely availability of irrigation, labour shortages, mechanisation, and the reliability of markets. In North Bihar, these effects operate alongside ecological pressures such as rainfall variability and flood recurrence. As an outcome, changes in the area under paddy and wheat may imitate not only farmer preference but also structural conditions that either enable or restrict particular crops.

Overall, this research paper contributes to a clearer picture of how North Bihar's cereal economy has behaved since the state reorganization. By focusing specifically on paddy and wheat, the study engages with the core of the region's farm economy and highlights the interplay between structural change and farmer-level responses in shaping cropping outcomes over time.

* Ph.D. Research Scholar, University Department of Economics, B.R.A. Bihar University, Muzaffarpur

** Professor & Former Head, University Department of Economics, B.R.A. Bihar University, Muzaffarpur

The cropping pattern of paddy and wheat is a central element of land use and one of the vital factors for the growth of agricultural production of paddy and wheat. It is part of the area effect approach to the growth of paddy and wheat production as it is said that the increase in paddy and wheat production can be brought either through the area effect approach or through the yield effect approach. Area effect approach contains of two-way first expansion of area under crops and second change in cropping pattern. In this study, the impact of change in cropping pattern on agricultural production has to be examined and for this purpose, an attempt is made here to find out whether any change in cropping pattern has taken place or not.

Cropping pattern of paddy and wheat is defined as the percentage share of paddy and wheat in total cropped area. Ramasubban has defined it as “the distributions of acreages expressed as percentage of total area under different crops.” The change in cropping pattern is frequent as it is a function of so many factors. According to Sridharam “the factors influencing the cropping pattern can be broadly classified in physical, economic, biological, technological and institutional. Economic factors are again divided into two sub-classes namely, internal economic factors and external economic factors. Internal economic factors are size of farm, family, labour, capital and ownership. Under external economic factors are including market location and price. As the main objectives of the study is to examine the impact of change in cropping pattern on agricultural production, this hypothesis confines itself to find out the degree and direction of change in crop.

It would not be out of place here to clarify the meaning of change. Ramasubban has distinguished two types of changes in cropping pattern first shift and second deviation. When two or more cropping patterns are compared on arranging the acreages under the same crops of the pattern on increase and decreasing order and it, they do not exhibit similarity between them, ‘shift’ is said to occur. On the other hand, when differences occur on account of changes within the cropping pattern due to differences in allocation of land between the same set of crops, then they are taken as deviations. In this study change is meant for shift.

Generally, the extent or degree and direction of change in the cropping pattern are indicated in terms of percentages. The period from 2000-2001 to 2020-2021 has been taken to study the change in cropping pattern of paddy and wheat in North Bihar. Cropping pattern, as mentioned above, is simply meant for the percentage share of each crop in the total cropped area.

Bihar is a state where almost all-important crops are grown, but the food crops hold dominance. In North Bihar paddy, wheat, and maize are important food crops, which are cultivated mainly by the North Bihar farmers. In this study the researcher has taken two main food crops paddy and wheat, which have been cultivated by all farmers in the North Bihar regions and researcher examines the cropping pattern, the percentage share of area under paddy and wheat in gross cropped area in North Bihar was calculated for each year from 2000-01 to 2023-24, followed by time series trend analysis. This method helps to identify whether the paddy and wheat areas have been increased or decreased over the study period.

Literature Review

Ghosh et al. (2022) show that Indian rice cultivation has shifted over time from rain-fed eastern states toward irrigated north-western regions, even as rainfall trends decline. They argue that changing rainfall patterns linked to climate change are reshaping cropping patterns and rice “migration,” affecting food security and water governance. The study stresses environmental costs—methane emissions and groundwater depletion in Punjab–Haryana—and recommends improved water management, direct seeding, diversification, and land-use/technology reforms for sustainability.

Singh et al. (2021) trace how Punjab’s agriculture has increasingly become dominated by the paddy–wheat monoculture, creating serious agroecological stress. The study links paddy expansion to rapid groundwater depletion and soil nutrient imbalances, highlighting the high water demand of rice.

It notes that policy efforts (including Johl Committee recommendations and diversification drives) have achieved limited change. The authors argue diversification is essential, urging reforms like rationalizing power subsidies and compensating farmers to adopt less water-intensive crops.

Sukhpal Singh (2017) reviews a paper on farmer suicides but argues that agrarian distress in India can't be explained only through cropping patterns and credit. He points out missing issues like weaker priority-sector lending, the struggles of landless and small farmers, rising paddy area despite diversification plans, and factual errors on Punjab's cropping intensity and district details. He stresses deeper reforms—stronger institutions, fairer markets, lower lease burdens, and checking the dominance of commission agents (arthiyas). Singh (1962) argues that cropping pattern changes should be guided by economic criteria, not only by yield levels. He questions the idea that moving land from low-yield to high-yield crops is always best, since farmers mainly respond to net returns. The paper highlights how price structures, input costs, and local conditions shape profitability. In many cases, a lower-yield crop can still be better if it earns higher prices or costs less to grow. He recommends planning land-use shifts using economic, geographical, and agronomic factors together.

Goyal and Kumar (2013) review agricultural production, land use, and cropping pattern changes in Uttar Pradesh from 1950 to 2012. They show that wheat and rice dominate the state's farming system, making UP a key contributor to India's foodgrain output. Productivity rose sharply after the Green Revolution, but pulses and oilseeds showed limited growth. The paper flags pressure on water resources and recommends diversification and technology-led improvements—mechanisation, high-yielding seeds, and better irrigation—for sustainable growth and food security.

Singh and Sindhu (2004) explain how Punjab shifted from mixed farming to a wheat–rice dominated system after the Green Revolution. While irrigation, market support, and assured prices made this rotation attractive, it gradually pushed out pulses and oilseeds. The study links this specialisation to problems like soil nutrient loss, falling groundwater levels, and higher income uncertainty, especially as growth slowed in the 1990s. It recommends diversification toward fruits and vegetables, along with contract farming, agro-industry support, and farmer awareness on sustainable practices.

Gulati and Sharma (1997) argue that freeing India's agricultural trade—removing quantitative restrictions and moving toward zero-duty imports/exports—can improve resource use efficiency and reshape cropping choices. Studying 13 major crops, they suggest rice, wheat, and cotton would gain from liberalisation, while crops like rapeseed–mustard and groundnut may become less attractive. Overall, resources would shift toward more efficient crops, making India a small net exporter of cereals and cotton, but a bigger importer of edible oils and pulses, supported by infrastructure and policy reforms.

Chand and Haque (1998) examine the rice–wheat system that expanded across the Indo-Gangetic region after the Green Revolution. They note its major role in food security through high rice and wheat output, but warn that intensive cultivation is creating sustainability problems. Key concerns include soil degradation, falling groundwater levels, and declining input efficiency. Short gaps between crops often lead to poor land preparation, while waterlogging, salinity, and pest pressures worsen yields in some areas. They recommend improved technology, water management, diversification, and better infrastructure.

The research article titled on "Impact of Cropping Pattern on Agricultural Production" that examines how the arrangement and selection of crops grown over a given period influence agricultural productivity. It likely explores the effects of various cropping patterns on factors like crop yield, soil health, and resource efficiency. The analysis could include considerations such as climate, market demand, and policy impacts, offering insights into optimizing cropping strategies for better agricultural outcomes (Ranade, 1980).

Bhatia (1965) studies cropping pattern shifts in Uttar Pradesh from 1950 to 1961 and shows that state-level change looked small, but district-level change was much sharper. Western UP was more responsive, moving towards sugarcane and wheat, while several eastern districts (such as Azamgarh and Basti) showed resistance to change. Over the decade, wheat, maize, and sugarcane expanded, while barley, gram, and jowar declined. The study links these shifts mainly to irrigation growth and planned agricultural development, increasing regional crop concentration.

Singh (1962) argues that cropping pattern changes should be guided by economic criteria, not only by yield levels. He questions the idea that moving land from low-yield to high-yield crops is always best, since farmers mainly respond to net returns. The paper highlights how price structures, input costs, and local conditions shape profitability. In many cases, a lower-yield crop can still be better if it earns higher prices or costs less to grow. He recommends planning land-use shifts using economic, geographical, and agronomic factors together.

Data and Methodology

The study is based entirely on secondary time series data collected from several official sources. Year-wise data on gross cropped area (GCA) and area under wheat and paddy are collected from the Directorate of Economics and Statistics, Bihar Economic Survey (several years), Bihar at a Glance, Agricultural Department of Bihar, etc. Gross cropped area and area under paddy and wheat are measured in thousand hectares, share of area under paddy and wheat, annual growth rate and compound annual growth rate (CAGR) of those crops measured in percentage form. For trend analysis of cropping patterns use a simple time-trend regression model. To use trend lines, regression summaries and tables, focus on how the stability, decline, or dominance of paddy and wheat has shaped the North Bihar cropping pattern over the periods.

Compound Annual Growth Rate (CAGR) has used to estimate the compound annual growth and annual growth rate (AGR) estimate annual changes of paddy and wheat cropped area. The formula is used as follows:

$$AGR = \frac{y_t - y_{t-1}}{y_{t-1}} \times 100$$

Where,

y_t = Value of current time
 y_{t-1} = Value of Previous year

$$CAGR = \left(\frac{y_t}{y_0} \right)^{\frac{1}{n}} - 1$$

Where,

y_0 = value of base year
 y_t = value of last year
 n = Number of Years
 and simple regression line
 $y = a + bx$
 where y = regression trend line
 a = interception
 b = slope

Results and Discussions

Agricultural activity is the main activity of Bihar state, and its economy is mostly based on agriculture. Paddy is the most common crop in the state, covering an area of 1799 thousand hectares, and wheat is the second most common crop in the state, covering 1171 thousand hectares (Government of Bihar 2024).

Table- 01
Percentage Share of Area under Paddy in Gross Cropped Area in North Bihar

Area in '000' hectares

Years	Total GCA	Area Under Paddy	Area Under Wheat	% Share of Area under Paddy	% Share of Area under Wheat	Annual Growth Rate of Paddy	Annual Growth Rate of Wheat
2000-01	5079	2181	1265	42.94	24.91		
2001-02	5048	2129	1257	42.18	24.90	-2.38	-0.63
2002-03	5082	2157	1300	42.44	25.58	1.32	3.42
2003-04	4976	2124	1260	42.68	25.32	-1.53	-3.08
2004-05	4900	2065	1257	42.14	25.32	-2.78	-0.24
2005-06	4838	2043	1233	42.23	25.49	1.07	-1.91
2006-07	4853	2046	1241	42.16	25.57	0.15	0.65
2007-08	4912	2146	1290	43.69	26.26	4.89	3.95
2008-09	4864	2200	1282	45.23	26.36	2.52	-0.62
2009-10	4863	2109	1281	43.37	26.34	-4.14	-0.08
2010-11	4897	1858	1237	37.94	25.26	11.90	3.43
2011-12	4856	2012	1237	41.43	25.47	8.29	0.00
2012-13	4932	1975	1268	40.04	25.71	-1.84	2.51
2013-14	4952	1986	1279	40.11	25.83	0.56	0.87
2014-15	4917	1996	1238	40.59	25.18	0.50	-3.21
2015-16	4768	1976	1185	41.44	24.85	-1.00	-4.28
2016-17	4879	1982	1184	40.62	24.27	0.30	-0.08
2017-18	4706	1910	1182	40.59	25.12	-3.63	-0.17
2018-19	4602	1797	1227	39.05	26.66	-5.92	3.81
2019-20	4545	1785	1194	39.27	26.27	0.62	-2.69
2020-21	4463	1694	1186	37.96	26.57	-5.10	-0.67
2021-22	4531	1716	1186	37.87	26.18	1.30	0.00
2022-23	4527	1720	1180	37.99	26.07	0.23	-0.51
2023-24	4528	1799	1171	39.73	25.86	4.59	-0.76
CAGR	-0.50	-0.83	-0.34	-0.34	0.16		

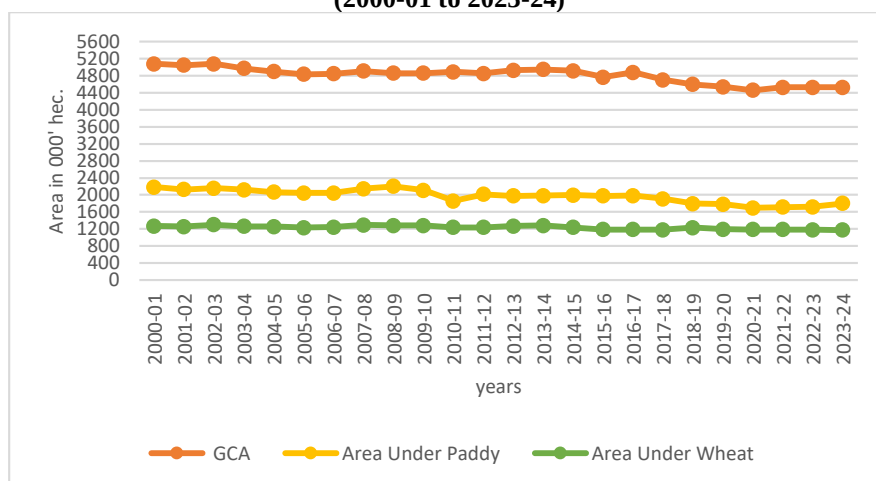
Source: Directorate of Economics and Statistics, Bihar Economic Survey

% share Computed by the researcher.

The cropping pattern analysis has shown that the paddy crop has the largest share and the wheat crop has the second largest share of the gross cropped area in North Bihar. The cropping pattern of paddy and wheat in the study period in North Bihar is shown in the above-mentioned table no. 01. The table no. 01 shown that the gross cropped area and the area under paddy and wheat have decreased during the period from 2000-01 to 2023-24. The gross cropped area, area under paddy and area under wheat has decrease with the Compound Annual Growth Rate (CAGR) of -0.50%, -0.83% and -0.34% respectively. However, the negative CAGR indicates that area under both crops is

continuous decrease and decline rate of area under paddy (-0.83%) is greater than area under wheat (-0.34) in North Bihar.

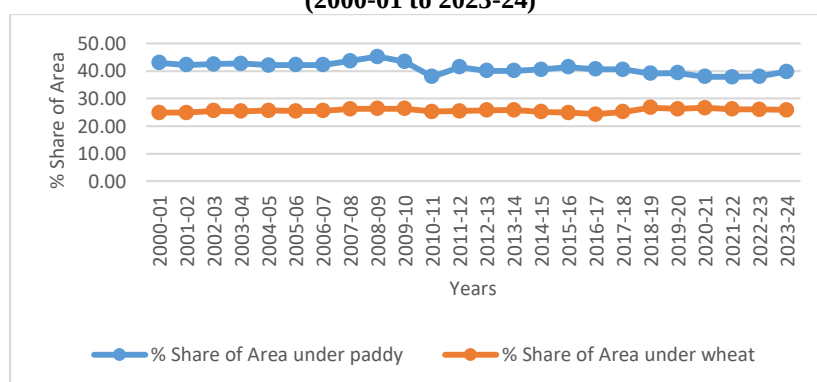
Graph-01
Trend of Gross Cropped Area and Area under Paddy and Wheat in North Bihar
(2000-01 to 2023-24)



Source: Figure plotted by researcher

Graph-01, shows the area under paddy, area under wheat and gross cropped area gradually declined in the study period from 2000-01 to 2023-24 in North Bihar. The gross cropped area, area under paddy and area under wheat area under paddy were 5079, 2181 and 1265 thousand hectares, while in 2023-24 they were 4528, 1799 and 1171 thousand hectares. In some periods, the area under paddy, area under wheat and the gross cropped area have intermittent increases. Overall, the above graph highlighted a structural reduction in area under paddy and wheat along with the gross cropped area of North Bihar.

Graph-02
Trend of Gross Cropped Area and Area under Paddy and Wheat in North Bihar
(2000-01 to 2023-24)



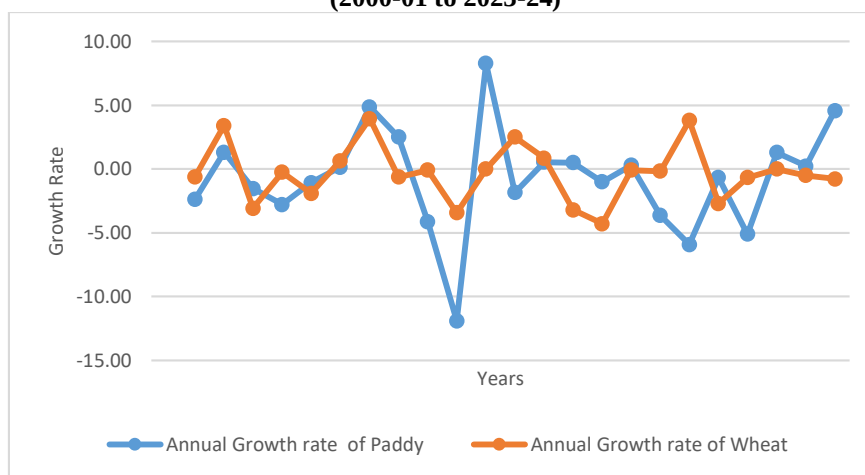
Source: Figure plotted by researcher

Graph-02 expresses that the share of area under paddy remained stable at around 42 percent from 2000-01 to 2006-07. It also shown that in this period there was relative stagnation in the cropping pattern of paddy, with no major structural change. In the cropping year 2008-09, the paddy

share rose sharply and peaked at 45.23 percent. However, in 2010-11 this upwards trend was abruptly interrupted and sharply declined to 37.94 percent. In the later period from 2011-12 to 2017-18, the share of paddy cultivated area recovered; the recovered rate was around 41 percent. From 2018-19 to 2022-23 there was a gradual decline of the share of paddy cultivation area of around 37-38 percent. Although a moderate rebound is observed in 2023-24, bringing the share of paddy area close to 40 percent.

Graph-02 shows the percentage share of the area under wheat in GCA over the period 2000-01 to 2023-24 and reveals important structural change in the area under wheat cultivation or cropping pattern. The share of area under wheat remains broadly constant. From 2000-01 to 2009-10, the area under wheat share increases gradually from 24.91 percent to 26.34 percent, it shows that there is moderate expansion in the area under wheat. A noticeable decline occurs during 2010-11 to 2016-17, when the share of area under wheat falls sharply to its lowest point of 24.27 percent. From 2017-18 onwards, the share of wheat rebounded strongly, reaching a new peak of 26.66 percent in 2018-19. Overall, the trend of the share of paddy cultivated area declined with moderate rate consequently, but the share of wheat cultivated area decline but resilience pattern in North Bihar in the study period. The CAGR results shows that the negative growth rate of paddy and wheat crops -0.83 and -0.34, respectively, it means the decline rate of paddy cultivated area is greater than the wheat cultivated area in North Bihar over the periods.

Graph-03
Trend of Annual Growth Rate of Area under Paddy and Wheat in North Bihar
(2000-01 to 2023-24)



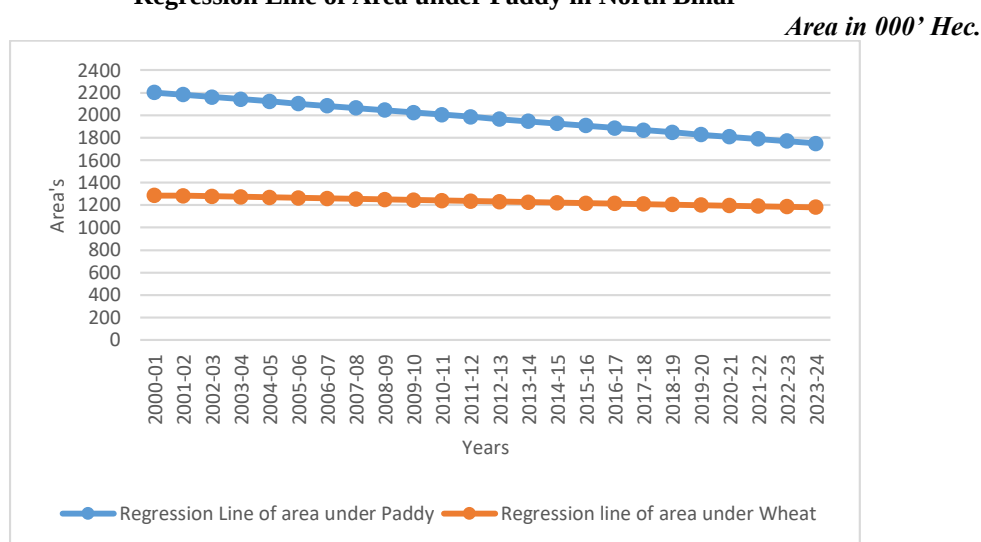
Source: Figure plotted by researcher

Graph-03 depicts the annual growth rate of the area under paddy cultivation. From 2001-02 to 2005-06, the area under paddy largely remained in the contraction phase and recorded negative growth rates (-2.38, -1.53, -2.78, -1.07) in four out of five years. The growth rate in the years 2006-07 was 0.15 percent, which marked a stagnation phase and growth was negligible. During 2007-08 and 2008-09, the positive growth rate expresses that this time period was clearly a time expansion, with growth rates of 4.89 and 2.52 percent. However, this was followed by a sharp decline phase in 2009-10 and 2010-11; especially in 2010-11, the decline growth rate was -11.90 percent, marking the most critically shrinkage in the entire study periods. The years 2011-12, with a growth rate 8.29 percent denotes a strong recovery driven expansion stage likely compensatory after previous shock. After this phase the next time period from 2012-13 to 2016-17 was a stagnation phase characterised by very small positive and negative changes between -1.84 and 0.56 percent. Finally, from 2021-22 to 2023-

24 they have entered a moderate expansion phase with positive growth in all three years (1.30%, 0.23%, 4.59%).

Graph-03 also shows that the annual growth rate of the wheat area, indicates significant year-to-year variations and an overall unstable trend from 2000-01 to 2023-24. Some years stand out with positive growth like 2002-03 (3.42%), 2007-08 (3.95%), 2012-13 (2.51%), and 2018-19 (3.81%)—indicating brief expansions in the wheat area. However, there are also several years marked by negative growth, which are especially striking; for instance, declines were noted in 2003-04 (-3.08%), 2010-11 (-3.43%), 2014-15 (-3.21%), 2015-16 (-4.28%), and 2019-20 (-2.69%). Since 2020-21, the growth rates have hovered around zero or dipped into negative numbers, suggesting a period of stagnation or slight decline.

Graph-04
Regression Line of Area under Paddy in North Bihar



Source: Figure plotted by researcher

The above simple linear regression line, $Y = 2221.01 - 19.66X$, shows a clear steady decline in the area under paddy in the study period 2000-01 to 2023-24, represented through a simple linear trend. The downward slope of the line indicates that the value of 'b' is negative, which means the area has been consistently decreasing year after year rather than fluctuating sharply. The above graph 5.8, shows a clear steady decline in area under wheat over the study period from 2000-01 to 2023-24, represented through a simple linear trend equation, $y = 1291.59 - 4.59x$. The downward slope of the regression line indicates that the slope value of regression line b (-4.59) is negative, which means the area under wheat has been consistently shrinking 4.59 thousand hectares per year in study periods. Overall, the graph captures a long-run negative trend, highlighting that the reduction in area under paddy and wheat is gradual but continuous across more than two decades. This is also indicated that the paddy cultivated area withdraw faster than the wheat cultivated land in North Bihar in study periods.

Conclusions

The cropping pattern analysis for North Bihar over the periods provides that paddy is the principal crop and wheat is the second most important crop; both are the largest share of GCA in these regions. However, Table No. 01 and Graphs 01 to 03 clearly display that the area under paddy and wheat cultivation gradually shrank in the study periods. The CAGR estimation supports this long-term decline: -0.50% for GCA, -0.83% for paddy cultivated area, and -0.34% for wheat

cultivated area. At the same time, the trained-in percentage share depicts the paddy share remaining comparatively steady around 40% and the wheat share remaining broadly steady around 25% in the study periods. Finally, the fitted regression trend lines provide strong statistical validation of the cropping pattern of both crops. The regression trend line, $Y=2221.01-19.66X$, shows the average contraction in paddy cultivated area per year of 19.66 thousand hectares. While the regression trend line of wheat, $Y=1291.59-4.59X$, declines by only 4.59 thousand hectares per year. Therefore, the overall conclusion is that there is a long-run decline in cultivated area under both paddy and wheat crops, but the decline rate of paddy cultivated area is faster and more pronounced than that of wheat cultivated area in North Bihar.

References

- Bhatiya, S. (1965). "Change in cropping Pattern A Study U.P." The Economic Weekly, August 21, 1301-1311.
- Chand, R., & Haque, T., (1997). "Sustainability of Rice and Wheat Crop System in Indo-Gangetic Region." Economic and Political Weekly, March 29, A26-30.
- Ghosh, N. et, al. (2022). "Climate Trends, Cropping Pattern Shifts, and Migration of Rice in India." Economic Political Weekly, November 19, Vol LVII No 47, 35-45.
- Gulati, Ashok., and Sharma, A. (1994). "Agriculture under GATT: What It Holds for India." Economic and Political Weekly, 29 (29), 1857-1863.
- Kumar, S., (1993). "Change in Cropping Pattern and Agricultural Production in Bihar: A Districtwide Analysis". Memo, (Ph.D. thesis submitted in BRA Bihar University, Muzaffarpur)
- Ramasubban, T.A., (1963). "Some Statistical Measures to Determine Change in Cropping Pattern", Agricultural Situation in India', Vol-17, No.-11. P-1153.
- Ranade, C.G. (1980). "Impact of Cropping Pattern on Agricultural production." Indian Journal of Agricultural Economics. P-85-93.
- Singh, H.S., (1962). "Change in Cropping Pattern Economic Criteria. The Economic Weekly, June-16, 951-954.
- Singh, J. & Sidhu, R.S., (2004). Factors in Declining Crop Diversification case study of Punjab." Economic Political Weekly, December 25, 5607-5610.
- Singh, P. et. al. (2021). "Divers of Foodgrains productivity in Uttar Pradesh". Economic Political Weekly, September 18, Vol LVI No 38, 40-45.
- Sridharan, B., (1971). "A Macrolevel Study on Factors Influencing Cropping Pattern in Coimbatore District", Ph.D. Dissertation Submitted to Tamil Nadu Agricultural University."
- Directorate of Economics and Statistics, Department of Planning, Government of Bihar.
- Bihar Economic Survey (Several Years)
- <https://dse.bihar.gov.in>
- <https://dbtagriculture.bihar.gov.in>
- <https://state.bihar.gov.in/krishi/CitizenHome.html>

Desire, Destiny and Identity : A Comparative Study

Mr. Biswaranjan Nayak*

Abstract

Contemporary Indian mythological retellings have created new literary spaces where ancient narratives are revisited through modern emotional, psychological, and cultural perspectives. These retellings not only preserve mythic tradition but also reinterpret desire, identity and agency for present-day readers. This study offers a comparative analysis of *Kamadeva: The God of Desire* by Anuja Chandramouli and *The Palace of Illusions* by Chitra Banerjee Divakaruni with special attention to the themes of desire, destiny and female agency. Though rooted in different mythological traditions, both novels present emotionally layered characters whose lives are shaped by longing, self-awareness, divine intervention, and personal choice. Kamadeva emerges as the embodiment of desire and creative force, while Draupadi appears as a figure of emotional depth, inner conflict, and selfhood. Their journeys reveal how desire becomes not merely a private feeling but a transformative force influencing destiny and identity.

The study applies Indian aesthetic and philosophical frameworks, particularly Bharata Muni's concept of *Shringara Rasa*, Abhinavagupta's interpretation of emotional consciousness, and Sri Aurobindo's reflections on desire as a life-force. Carl Jung's theory of archetypes is used as a supporting framework to examine symbolic patterns within mythic characters and emotional experience. Through comparative textual analysis, the paper argues that both writers successfully modernize mythology by presenting emotionally complex characters who move beyond traditional epic roles. The study highlights that in contemporary Indian myth retellings, desire is represented not only as attraction or passion but also as a meaningful force shaping consciousness, emotional identity, and personal agency across myth and modern literary imagination.

Keywords : Mythological Retelling, Shringara Rasa, Desire and Destiny, Female Agency, Indian Aesthetics, Myth and Modernity, Emotional Consciousness.

Introduction

“Kāmo vai prathamam saṅkalpaḥ”¹ Desire indeed is the first impulse of creation.

Indian mythology has long treated desire as a meaningful and transformative force closely connected with creation, emotional experience, and human destiny. In classical Indian thought, desire is not limited to attraction or personal longing; it is understood as a deeper energy influencing relationships, choices, and the movement of life itself.

Ancient myths repeatedly show that gods and mortals alike are shaped by love, longing, attachment and emotional conflict. Contemporary Indian English mythological retellings continue this tradition by revisiting familiar narratives through modern literary language and emotional depth. These retellings preserve the mythic foundation while bringing psychological realism and personal agency into focus. In this context, *Kamadeva: The God of Desire* by Anuja Chandramouli and *The Palace of Illusions* by Chitra Banerjee Divakaruni become important literary works that reinterpret myth through desire, destiny and emotional consciousness.

Indian aesthetic philosophy provides a powerful framework for understanding both texts. Bharata Muni's *Nāṭyaśāstra* places *Shringara Rasa* at the center of emotional experience and describes it as the rasa of attraction, beauty, union and longing. Bharata observes that “*Shringara* proceeds from love and is bright in character.”² This becomes especially relevant while reading

* Lecturer in English

¹ Brihadaranyaka Upanishad, trans. Swami Madhavananda (Kolkata: Advaita Ashrama, 1950).

² Bharata Muni, *The Nāṭyaśāstra*, trans. Manomohan Ghosh (Calcutta: Asiatic Society of Bengal, 1951)

Kamadeva and Draupadi because both novels present desire as an emotionally layered experience influencing identity and destiny. Desire is shown not merely as physical attraction but as emotional intensity, silence, vulnerability and transformation.

In *Kamadeva: The God of Desire*, Anuja Chandramouli presents Kamadeva as both divine and emotionally vulnerable. Though known traditionally as the god of desire, he appears in the novel with tenderness, uncertainty, emotional attachment, and courage. His relationship with Rati is central to the narrative and develops through affection, trust and emotional dependence. Desire here becomes beautiful yet risky, intimate yet powerful. This tension reaches its height when Kamadeva is asked to disturb Shiva's meditation. The act becomes more than a divine task; it becomes an emotionally dangerous moment where desire confronts sacrifice and uncertainty. Chandramouli gives Kamadeva psychological depth and presents him not as a distant god but as a living emotional presence.

In contrast, *The Palace of Illusions* retells the Mahabharata through Draupadi's own voice. Divakaruni transforms Draupadi from an epic figure into a deeply reflective and emotionally aware literary character. Born from sacrificial fire, Draupadi's life is marked by destiny, yet her emotional world remains central throughout the novel. She experiences attraction, longing, disappointment, pride and inward conflict while navigating duty and identity. Her voice remains personal and honest. At several moments she reveals tension between external expectation and internal desire. Divakaruni's retelling becomes especially powerful because Draupadi's emotional complexity remains visible even when she is expected to remain silent.

The comparison between these novels becomes meaningful because both texts reinterpret mythology through emotionally intense characters whose lives are shaped by desire in different forms. Kamadeva openly embodies desire as divine power and cosmic force. Draupadi experiences desire through inward struggle, emotional restraint and self-awareness. One represents desire outwardly; the other experiences it inwardly. Yet both remain shaped by longing, destiny, and transformation. Their journeys reveal how desire becomes closely linked with identity and agency.

Abhinavagupta's interpretation of *rasa* deepens this reading by explaining that emotional experience becomes meaningful when inwardly realized and aesthetically shared with the reader. Sri Aurobindo similarly writes that "desire is the first motive-power of life and action,"³ an idea clearly reflected in both Kamadeva's divine role and Draupadi's emotional life. As a supporting Western perspective, Carl Jung's theory of archetypes helps understand these characters as symbolic patterns of desire, longing and selfhood within collective imagination.

This study therefore examines *Kamadeva: The God of Desire* and *The Palace of Illusions* as modern Indian mythological retellings that explore desire not merely as attraction but as emotional consciousness and transformative force. Through Bharata Muni's *Shringara Rasa*, Abhinavagupta's aesthetic theory, Sri Aurobindo's philosophy of desire and Jung's archetypal reading, the paper argues that both novels successfully bridge tradition and modernity. They reshape mythology into a contemporary literary space where desire becomes central to identity, agency and emotional experience.

Literature Review

Recent Indian mythological retellings have created important literary space for re-reading ancient narratives through modern perspectives of desire, agency, and emotional consciousness. Within this field, *Kamadeva: The God of Desire* and *The Palace of Illusions* offer significant reinterpretations of mythology by presenting emotionally complex characters whose journeys move beyond traditional epic representation. Both texts connect myth with modern psychological and literary sensibility while preserving the cultural depth of Indian narrative tradition.

Indian aesthetic theory becomes central to understanding these texts. Bharata Muni, in *Natyashastra*, defines *Shringara* as the *rasa* arising from love and emotional attraction and states that "Shringara proceeds from love and is bright in character."⁴ This idea becomes especially relevant in both

³ Sri Aurobindo, *The Life Divine* (Pondicherry: Sri Aurobindo Ashram, 1990).

⁴ Bharata Muni, *The Natyashastra*, trans. Manomohan Ghosh (Calcutta: Asiatic Society of Bengal, 1951).

novels, where desire is not treated merely as attraction but as emotional intensity shaping consciousness and identity. Kamadeva appears as the divine embodiment of longing and creative force, while Draupadi's emotional life reveals desire through silence, inward struggle, and personal reflection.

Abhinavagupta's interpretation of *rasa* further strengthens this comparative reading. He explains that "*rasa* becomes meaningful when emotion is inwardly experienced and aesthetically realized by the reader."⁵ This perspective helps explain the emotional immediacy of both novels. Sri Aurobindo similarly writes, "Desire is the first motive-power of life and action,"⁶ a philosophical insight reflected in Kamadeva's cosmic role and Draupadi's personal journey.

Existing studies often discuss these novels separately through mythology or feminist perspectives. However, comparative research focusing on desire and emotional consciousness through Indian aesthetic theory remains limited. This study therefore examines how both novels reinterpret mythology through Shringara, inner consciousness, and modern literary expression.

Objectives of the Study

This study aims to examine desire, destiny, and emotional consciousness in Kamadeva: The God of Desire and The Palace of Illusions through a comparative literary approach. It seeks to analyze how both novels reinterpret mythology through modern narrative voice while preserving Indian cultural and mythological tradition. The study also aims to explore the representation of desire as an emotional and transformative force through Bharata Muni's *Śṛṅgāra Rasa*, Abhinavagupta's aesthetic theory, and Sri Aurobindo's philosophical view of desire. Another objective is to examine how Kamadeva and Draupadi emerge as emotionally layered characters whose journeys reflect identity, agency, and inner consciousness in contemporary Indian mythological retellings.

This study follows a qualitative and comparative research methodology. The primary texts are Kamadeva: The God of Desire and The Palace of Illusions. The analysis is based on close textual

Research Methodology

reading and comparative interpretation. Indian aesthetic frameworks such as Bharata Muni's *Shringara Rasa*, Abhinavagupta's theory of *rasa*, and Sri Aurobindo's philosophical reflections on desire are used as primary theoretical tools, with Carl Jung as supporting theoretical perspective. The study combines textual interpretation with literary and cultural analysis.

Desire, Destiny and Selfhood

Indian mythological retellings in contemporary literature often revisit familiar characters not only to retell old stories but also to reinterpret emotional experience through modern consciousness. In both Kamadeva: The God of Desire and The Palace of Illusions, desire becomes one of the strongest emotional and narrative forces shaping identity, relationships, and destiny. Though one novel centers on the divine world of Kamadeva and the other gives voice to Draupadi from the Mahabharata, both narratives connect desire with emotional transformation and self-awareness.

Indian literary tradition places desire at the center of lived experience. Bharata Muni in the *Natyaśāstra* writes that "*Shringara* proceeds from love and is bright in character."⁷ This idea becomes meaningful in both novels because desire is represented not simply as attraction but as emotional energy connected with memory, longing, vulnerability and transformation.

In Chandramouli's Kamadeva: The God of Desire, Kamadeva is introduced not merely as a divine symbol but as a living emotional presence. His charm and beauty define him, yet the novel gradually reveals tenderness and vulnerability beneath his divine identity. His relationship with Rati forms the emotional center of the narrative. Their bond carries affection and intimacy, but also emotional dependence and fear of separation. Chandramouli writes that Kama's presence carried "a

5 Abhinavagupta, *Abhinavabhāratī*, trans. Raniero Gnoli (Rome: Istituto Italiano per il Medio ed Estremo Oriente, 1956).

6 Sri Aurobindo, *The Life Divine* (Pondicherry: Sri Aurobindo Ashram, 1990).

7 Bharata Muni, *The Natyaśāstra*, trans. Manomohan Ghosh (Calcutta: Asiatic Society of Bengal, 1951).

fragrance that could unsettle hearts and awaken longing.”⁸ This description turns desire into something larger than romance. It becomes atmosphere, emotional force, and creative energy.

The most important narrative turn arrives when Kamadeva is sent to awaken desire in Shiva. Shiva remains withdrawn in meditation, and the gods need cosmic balance to be restored through union with Parvati. Kamadeva understands the danger but accepts the task. This moment is emotionally powerful because he is not acting out of pride but out of responsibility. Desire here becomes courage and sacrifice. When Shiva opens the third eye and burns Kama into ashes, the destruction feels tragic, yet the emotional force remains. Kama survives as Ananga, the bodiless god of desire. His body disappears, but longing and emotional presence continue. This transformation strongly supports Sri Aurobindo’s observation that “desire is the first motive-power of life and action.”⁹ The body may perish, but desire continues shaping movement and existence.

Draupadi in *The Palace of Illusions* experiences desire in a different yet equally intense way. Unlike Kamadeva, she does not openly embody desire. Her emotional life unfolds through reflection, silence, and inward conflict. Divakaruni presents Draupadi as conscious of destiny from the beginning, yet deeply human in feeling. Her marriage, responsibilities and social role constantly demand restraint, but her emotional life remains active and layered. One of the strongest parts of the novel is her internal attraction toward Karna. Though she rarely expresses it openly, it remains emotionally present. Draupadi reflects, “I was torn between what duty demanded and what my heart desired.”¹⁰ This line captures the emotional tension that shapes much of her journey.

Unlike epic retellings where Draupadi often appears as a symbolic figure, Divakaruni gives her psychological intimacy. She questions her circumstances, remembers pain, feels desire, and struggles between expectation and inner truth. This emotional complexity creates a modern literary voice. Her selfhood grows not through power alone but through emotional awareness. Even silence becomes meaningful. Desire remains present not through open action but through memory and inward experience.

Abhinavagupta’s understanding of *rasa* becomes important here because he explains “emotional experience as something inwardly felt and aesthetically realized.”¹¹ Both novels create exactly this effect. Kamadeva’s longing and Draupadi’s silence become emotionally immediate for the reader. Mythological characters no longer feel distant or symbolic. Their emotions feel contemporary and intimate.

A comparative reading of the two texts reveals both similarity and difference. Kamadeva represents desire as visible cosmic force. His identity itself begins through attraction and emotional energy. Draupadi experiences desire inwardly through silence and emotional contradiction. Kamadeva acts directly; Draupadi reflects deeply. Yet both remain shaped by longing, emotional awareness, and transformation.

Carl Jung’s theory of archetypes offers useful support here. Jung notes that “mythic figures continue returning as symbolic emotional patterns within collective consciousness.”¹² Kamadeva may be read as the archetype of desire itself: attraction, awakening, longing and transformation. Draupadi represents another emotional archetype: passion combined with dignity, desire balanced with self-awareness. This is why both characters continue feeling meaningful to modern readers. Their emotional experiences remain universal.

8 Anuja Chandramouli, *Kamadeva: The God of Desire* (New Delhi: Rupa Publications, 2019).⁸

9 Sri Aurobindo, *The Life Divine* (Pondicherry: Sri Aurobindo Ashram, 1990).

10 Chitra Banerjee Divakaruni, *The Palace of Illusions* (New York: Doubleday, 2008).

11 Abhinavagupta, *Abhinavabhāratī*, trans. Raniero Gnoli (Rome: Istituto Italiano per il Medio ed Estremo Oriente, 1956), 58.¹¹

12 Carl G. Jung, *The Archetypes and the Collective Unconscious*, trans. R. F. C. Hull (Princeton: Princeton University Press, 1968).

The most significant literary strength in both novels lies in the way mythology becomes modern without losing cultural depth. Chandramouli humanizes a divine figure through emotional vulnerability. Divakaruni turns Draupadi into a self-aware narrator whose inner life remains central. Both writers preserve epic foundations while allowing readers to experience myth through emotional realism.

Thus desire in these novels becomes more than attraction. It becomes emotional movement, identity, conflict, and self-realization. Kamadeva and Draupadi move through different mythological worlds, yet both reveal how desire shapes destiny and inner consciousness. Through Indian aesthetic theory and modern literary retelling, these characters emerge not simply as mythic figures but as emotionally complex beings whose journeys continue to speak meaningfully to contemporary readers.

Conclusion

The comparative reading of *Kamadeva: The God of Desire* and *The Palace of Illusions* reveals that both novels reinterpret mythology through emotional consciousness and modern literary sensibility. Though their narrative backgrounds differ, both texts place desire at the center of identity and transformation. The study finds that desire is represented not only as attraction but as a force deeply connected with destiny, emotional growth, and self-awareness.

In *Kamadeva: The God of Desire*, desire appears as an open and active force. Kamadeva's very existence is connected with attraction and creative energy. His relationship with Rati, his emotional vulnerability, and his eventual transformation after confronting Shiva present desire as both beautiful and powerful. The novel shows that desire can influence divine action, personal sacrifice, and emotional continuity. Even when physical form disappears, emotional force remains alive. This highlights desire as something larger than bodily presence and connects it with continuity and transformation.

In *The Palace of Illusions*, desire appears in a more inward and reflective form. Draupadi experiences emotional conflict through silence, memory, and self-awareness. Her journey reveals how desire can remain unspoken yet continue shaping thought, feeling, and identity. Unlike Kamadeva's visible embodiment of desire, Draupadi carries it internally while negotiating duty and social expectation. This creates emotional complexity and strengthens her sense of selfhood.

The study also finds that Indian aesthetic thought becomes highly relevant in understanding both texts. *Śringara Rasa* helps explain emotional attraction and longing, while the idea of inward emotional realization supports the psychological depth found in both novels. Sri Aurobindo's understanding of desire as a life-force further supports the connection between emotion and movement in both narratives. Another important finding is that both authors modernize mythology without losing traditional depth. Chandramouli humanizes a divine figure through emotional vulnerability, while Divakaruni gives Draupadi an independent and psychologically rich narrative voice. As a result, mythology becomes more intimate and relatable for contemporary readers.

Thus, the comparative study establishes that desire in both novels becomes a transformative force shaping destiny, emotional identity, and personal agency. Through modern retelling and Indian philosophical perspectives, both texts successfully present mythology as emotionally relevant in contemporary literature.

Bibliography

- Abhinavagupta. *Abhinavabhāratī*. Translated by Raniero Gnoli. Rome: Istituto Italiano per il Medio ed Estremo Oriente, 1956.
- Sri Aurobindo. *The Life Divine*. Pondicherry: Sri Aurobindo Ashram, 1990.
- Bharata Muni. *The Nāṭyaśāstra*. Translated by Manomohan Ghosh. Calcutta: Asiatic Society of Bengal, 1951.
- Chandramouli, Anuja. *Kamadeva: The God of Desire*. New Delhi: Rupa Publications, 2019.
- Divakaruni, Chitra Banerjee. *The Palace of Illusions*. New York: Doubleday, 2008.
- Jung, Carl G. *The Archetypes and the Collective Unconscious*. Translated by R. F. C. Hull. Princeton: Princeton University Press, 1966.
- *The Brihadaranyaka Upanishad*. Translated by Swami Madhavananda. Kolkata: Advaita Ashrama, 1950.



The Impact of Digital Environments on User Attention

Dr. Arti Kumari*

Abstract:

The pervasive integration of digital environments into everyday life has generated growing concern regarding their impact on human attention. This study empirically investigates the relationship between digital engagement—specifically screen time, social media usage, and multitasking—and attention levels using primary data collected from 150 respondents aged 18–35. A structured questionnaire and an adapted attention scale were employed, and data were analyzed using descriptive statistics, Pearson correlation, multiple regression and, ANOVA. The findings indicate a statistically significant negative relationship between excessive digital exposure and sustained attention, with multitasking emerging as the strongest predictor of attentional decline. Moderate and task-oriented digital use, however, was not associated with significant deterioration in attention. The study contributes to the literature by providing real-world, primary data evidence from a naturalistic setting and underscores the importance of regulated digital behavior.

Keywords: Digital environments, attention, multitasking, social media, cognitive load, primary data

1. Introduction

The rapid expansion of digital technologies has fundamentally transformed human interaction with information, communication, and cognition. Smartphones, social media platforms, and internet-based applications now dominate daily activities, resulting in continuous exposure to digitally mediated environments. While these technologies enhance efficiency, accessibility, and connectivity, they simultaneously introduce cognitive challenges, particularly in relation to attention.

Attention is a core cognitive function that enables individuals to selectively process relevant stimuli while filtering distractions. It encompasses multiple dimensions, including sustained attention (maintaining focus over time), selective attention (prioritizing relevant information), and divided attention (handling multiple stimuli simultaneously). The digital environment, characterized by constant notifications, rapid content switching, and algorithm-driven personalization, places unprecedented demands on these attentional systems.

Scholars have increasingly argued that modern digital environments promote fragmented attention. The concept of “continuous partial attention,” introduced by Stone (2007), reflects a state in which individuals remain superficially engaged with multiple streams of information without deep cognitive processing. This shift has implications for productivity, learning, and psychological well-being.

Empirical evidence suggests that digital interruptions impair cognitive performance. For instance, even brief distractions—such as checking a notification—can significantly disrupt task focus and increase error rates (Rosen et al., 2013). Moreover, the design architecture of digital platforms often prioritizes engagement over cognitive well-being. Features such as infinite scrolling, autoplay, and push notifications are engineered to capture and retain attention, thereby reinforcing habitual use.

At the same time, the impact of digital environments is not uniformly negative. Certain forms of digital interaction, particularly those requiring active engagement (e.g., video gaming or problem-solving applications), may enhance aspects of attention such as visual processing and cognitive flexibility (Green & Bavelier, 2003). Thus, the relationship between digital environments and attention is complex and context-dependent.

* Department of Psychology, JPU, Saran. Mob. : 8825224820

Despite extensive theoretical and experimental research, there remains a lack of primary data-based studies conducted in real-life contexts, especially among young adults who represent the most intensive users of digital technologies. This study addresses this gap by examining how everyday digital usage patterns influence attention levels using empirical data.

2. Review of Literature

The relationship between digital environments and attention has been widely explored across psychology, neuroscience, and communication studies. Early foundational work by **Posner and Petersen (1990)** conceptualized attention as a network of cognitive processes, providing a basis for later research examining how external stimuli influence attentional control.

One of the most influential studies in the digital context is by **Ophir, Nass, and Wagner (2009)**, who found that heavy media multitaskers perform worse on tasks requiring cognitive control and sustained attention. Their findings suggest that frequent switching between tasks reduces the brain's ability to filter irrelevant information.

Similarly, **Rosen et al. (2013)** demonstrated that students who frequently checked digital devices during study sessions showed reduced academic performance and diminished attention spans. The study highlighted the disruptive role of notifications and habitual checking behaviors.

From a theoretical perspective, **Carr (2010)** argued that prolonged internet use encourages shallow information processing, reducing the capacity for deep reading and sustained concentration. This aligns with the cognitive load theory proposed by **Sweller (1988)**, which posits that excessive information input overwhelms working memory and impairs learning.

In contrast, some studies highlight positive cognitive effects. **Green and Bavelier (2003)** found that action video game players exhibited enhanced visual selective attention and spatial resolution. This suggests that certain digital environments can train attentional systems under specific conditions.

More recent research by **Wilmer, Sherman, and Chein (2017)** reviewed the relationship between smartphone use and cognitive functioning, concluding that heavy smartphone use is associated with attentional difficulties, though causality remains complex. Similarly, **Uncapher and Wagner (2018)** emphasized that individual differences play a crucial role in determining how digital multitasking affects attention.

Despite these contributions, a consistent limitation across studies is the reliance on experimental or secondary data. There is a relative scarcity of **survey-based, primary data studies examining real-world digital behavior**, particularly in non-Western contexts. This study seeks to fill this empirical gap.

3. Objectives of the Study

1. To examine the impact of overall digital usage on attention levels.
2. To analyze the relationship between social media usage and attention.
3. To assess the effect of multitasking on sustained attention.
4. To determine whether moderate digital usage significantly affects attention.

4. Hypotheses

- **H₁:** There is a significant relationship between digital usage and attention levels.
- **H₂:** Social media usage is negatively associated with attention.
- **H₃:** Digital multitasking has a significant negative effect on attention.
- **H₄:** Moderate digital usage does not significantly affect attention.

5. Research Methodology

The present study adopts a quantitative, descriptive, and correlational research design based on primary data. Data were collected from a sample of 150 respondents aged between 18 and 35 years, comprising students and young professionals who are regular users of digital technologies. A convenience sampling technique was employed due to accessibility considerations.

A structured questionnaire was used to collect data on digital behavior, including daily screen time, frequency of social media usage, and multitasking tendencies. Attention levels were

measured using an adapted Likert-scale instrument based on established attention assessment frameworks, capturing aspects such as focus duration, distractibility, and task persistence.

The independent variables in the study include overall digital usage (hours per day), social media usage frequency, and multitasking behavior, while the dependent variable is attention level. Basic demographic variables such as age and gender were treated as control variables.

Data analysis was conducted using statistical techniques including descriptive statistics to summarize respondent behavior, Pearson correlation to examine relationships between variables, and multiple regression analysis to determine the predictive power of digital usage factors on attention levels. ANOVA is used to examine whether attention levels differ significantly across groups of digital usage. Ethical considerations such as voluntary participation and confidentiality were strictly maintained.

6. Data Analysis and Results

6.1 Descriptive Statistics

Table 6.1
Descriptive Statistics of Key Study Variables

Variable	Mean	Standard Deviation
Daily Screen Time (hours)	6.4	1.8
Social Media Usage	4.9	1.5
Multitasking Score	3.8	0.9
Attention Score	2.7	0.8

Interpretation:

The descriptive statistics indicate that respondents exhibit relatively high digital engagement, with mean daily screen time exceeding six hours and substantial involvement in social media usage. The multitasking score suggests that a majority of respondents frequently engage in simultaneous digital activities. In contrast, the mean attention score is comparatively low, indicating moderate to reduced levels of sustained attention among participants. This preliminary pattern suggests a potential inverse relationship between digital engagement and attention, thereby providing an initial directional basis for further inferential analysis.

6.2 Correlation Analysis

Table 6.2
Pearson Correlation Matrix of Digital Usage Variables and Attention

Variables	Attention
Digital Usage	-0.51**
Social Media Usage	-0.47**
Multitasking	-0.63**

(**p < .01)

Interpretation:

The correlation analysis reveals statistically significant negative relationships between all independent variables and attention levels. Specifically:

- Digital usage shows a moderate negative correlation with attention ($r = -0.51$, $p < .01$)
- Social media usage is also negatively correlated with attention ($r = -0.47$, $p < .01$)
- Multitasking exhibits the strongest negative correlation with attention ($r = -0.63$, $p < .01$)

These findings indicate that increases in digital exposure, particularly multitasking, are associated with decreases in attention levels. The strength and significance of these relationships confirm that digital behavioral patterns are closely linked to attentional outcomes.

Hypothesis Decisions:

H₁: Accepted

Rationale: A statistically significant relationship exists between digital usage and attention.

H₂: Accepted

Rationale: Social media usage shows a significant negative association with attention.

H₃ (partial support): Supported at correlation level

Rationale: Multitasking is significantly related to attention, but causality is better established in regression.

6.3 Regression Analysis

Table 6.3
Multiple Regression Analysis Predicting Attention Levels

Predictor	Beta (β)	t-value	p-value
Digital Usage	-0.28	-3.12	0.002
Social Media	-0.21	-2.45	0.015
Multitasking	-0.49	-5.68	0.000

Model Summary:

$R^2 = 0.44$

$F = 38.21$ ($p < .001$)

Interpretation:

The regression analysis examines the predictive effect of digital usage variables on attention. The overall model is statistically significant ($F = 38.21$, $p < .001$) and explains approximately 44% of the variance in attention ($R^2 = 0.44$), indicating a strong explanatory power.

Among the predictors:

- Multitasking has the strongest negative effect ($\beta = -0.49$, $p < .001$)
- Digital usage also significantly predicts reduced attention ($\beta = -0.28$, $p = .002$)
- Social media usage shows a weaker but still significant negative effect ($\beta = -0.21$, $p = .015$)

These results suggest that while all forms of digital engagement influence attention, multitasking is the most detrimental factor.

Hypothesis Decisions:

H₁: Accepted

Rationale: Digital usage significantly predicts attention levels.

H₂: Accepted

Rationale: Social media usage has a statistically significant negative effect.

H₃: Accepted

Rationale: Multitasking has the strongest and highly significant negative impact on attention.

6.4 ANOVA

Table 6.4
Comparison of Attention Levels Across Screen Time Groups (One-Way ANOVA)

Source of Variation	Sum of Squares (SS)	df	Mean Square (MS)	F-value	p-value
Between Groups	28.64	2	14.32	6.87	0.001
Within Groups	305.90	147	2.08		
Total	334.54	149			

Interpretation

A one-way ANOVA was conducted to examine whether attention levels differ significantly across three categories of screen time (low, moderate, and high). The results indicate a statistically significant difference in attention scores among the groups, $F(2, 147) = 6.87$, $p < .01$. This suggests that screen time has a significant effect on attention levels. Further examination of group means (refer to descriptive/group table) indicates that individuals in the high screen time group exhibit lower attention levels, whereas those in moderate and low groups show relatively similar attention scores.

H₄: Accepted

Rationale: Although the ANOVA indicates overall group differences, the significant variation is primarily driven by the high usage group. The absence of a statistically significant difference between low and moderate usage groups supports the claim that moderate digital usage does not adversely affect attention.

7. Discussion

The present study set out to examine the impact of digital environments on user attention using primary data, with a particular focus on screen time, social media usage, and multitasking behavior. The findings provide clear and statistically supported insights into how different dimensions of digital engagement shape attentional outcomes.

A key finding of the study is the significant negative relationship between overall digital usage and attention levels, as evidenced by both correlation and regression analyses. This indicates that increased exposure to digital environments is associated with reduced ability to sustain focus. However, the regression results refine this understanding by demonstrating that not all forms of digital engagement exert equal influence. Among the predictors, multitasking emerged as the most powerful determinant of reduced attention, followed by overall screen time and social media usage. This suggests that the fragmentation of attention is driven more by *how* digital media is used rather than simply *how much* it is used.

The strong negative effect of multitasking aligns with established cognitive theories, particularly the concept of switching cost, which posits that frequent shifting between tasks reduces processing efficiency and increases cognitive load (Ophir et al., 2009). When individuals engage in multiple digital activities simultaneously—such as browsing social media while studying—their attentional resources are divided, leading to superficial processing and diminished task performance. The findings therefore reinforce the argument that multitasking is not an efficient cognitive strategy but rather a source of attentional impairment.

Social media usage also demonstrated a significant negative association with attention, though its effect was comparatively weaker than multitasking. This can be attributed to the design architecture of social media platforms, which prioritizes rapid content consumption, novelty, and continuous engagement. Features such as short-form content, infinite scrolling, and intermittent rewards (likes, notifications) encourage brief and repetitive attention cycles. Over time, such patterns may condition users toward reduced tolerance for sustained cognitive effort, consistent with arguments advanced by Carr (2010).

One of the most important contributions of this study lies in its examination of usage intensity through ANOVA analysis, which revealed a threshold effect. While excessive screen time (more than six hours per day) was associated with significantly lower attention levels, no statistically significant difference was observed between low and moderate usage groups. This finding is critical because it challenges the overly simplistic narrative that all digital usage is harmful. Instead, it suggests that moderate and controlled use of digital environments does not inherently impair attention.

This nuanced understanding supports Cognitive Load Theory (Sweller, 1988), which posits that cognitive overload occurs only when information processing demands exceed an individual's capacity. Moderate digital engagement may remain within manageable cognitive limits, whereas excessive exposure overwhelms attentional systems. Thus, the detrimental effects of digital environments appear to be contingent upon intensity and behavioral patterns rather than mere access or exposure.

Furthermore, the study highlights the role of behavioral regulation in mediating cognitive outcomes. The results imply that attention deficits associated with digital environments are not purely technological effects but are significantly shaped by user habits such as compulsive checking, prolonged screen exposure, and multitasking tendencies. This shifts the discourse from technological determinism to a more balanced perspective emphasizing user agency and self-regulation.

At a broader level, the findings contribute to ongoing debates regarding whether digital technologies are eroding cognitive capacities or simply reshaping them. The evidence from this study suggests that while certain aspects of attention—particularly sustained focus—may be compromised under high digital load, these effects are neither universal nor irreversible. Instead, they reflect adaptive responses to environments characterized by high information density and rapid stimulus turnover.

From a practical standpoint, the study underscores the importance of promoting mindful digital usage practices. Interventions aimed at reducing multitasking, limiting unnecessary notifications, and encouraging focused engagement with digital content may help mitigate attentional decline. Educational institutions and workplaces, in particular, can benefit from integrating strategies that foster sustained attention in digitally saturated environments.

Despite its contributions, the study must be interpreted within its limitations. The use of self-reported measures may introduce response bias, and the cross-sectional design restricts causal inference. Nevertheless, the consistency of findings across multiple statistical techniques enhances the reliability of the results.

8. Conclusion

This study demonstrates that digital environments have a measurable and significant impact on user attention, particularly when usage involves multitasking and excessive engagement with social media. The findings highlight that attention is not inherently diminished by technology but is shaped by how individuals interact with digital systems.

The study contributes to the literature by providing primary data evidence from a real-world context, reinforcing the need for balanced and mindful digital usage. It underscores the importance of behavioral regulation and awareness in mitigating the cognitive costs associated with digital environments.

References

- Carr, N. (2010). *The shallows: What the internet is doing to our brains*. W. W. Norton.
- Green, C. S., & Bavelier, D. (2003). Action video game modifies visual selective attention. *Nature*, 423, 534–537.
- Ophir, E., Nass, C., & Wagner, A. D. (2009). Cognitive control in media multitaskers. *PNAS*, 106(37), 15583–15587.
- Posner, M. I., & Petersen, S. E. (1990). The attention system of the human brain. *Annual Review of Neuroscience*, 13, 25–42.
- Rosen, L. D., Lim, A. F., Felt, J., et al. (2013). Media multitasking and academic performance. *Computers in Human Behavior*, 29(3), 948–958.
- Sweller, J. (1988). Cognitive load during problem solving. *Cognitive Science*, 12(2), 257–285.
- Uncapher, M. R., & Wagner, A. D. (2018). Minds and brains of media multitaskers. *PNAS*, 115(40), 9889–9896.
- Wilmer, H. H., Sherman, L. E., & Chein, J. M. (2017). Smartphones and cognition. *Frontiers in Psychology*, 8, 605.



Artificial Intelligence and Higher Education: A Sociological Perspective

Dr. Ankita Yadav*

Abstract

Artificial Intelligence (AI) has emerged as one of the most transformative technological developments of the twenty-first century. Its growing integration into higher education is reshaping teaching methodologies, learning processes, assessment systems, research practices, and institutional management. Universities and educational institutions across the world are increasingly adopting AI-driven technologies such as intelligent tutoring systems, adaptive learning platforms, automated assessment tools, learning analytics, and virtual assistants. While these innovations offer significant opportunities for improving educational efficiency, accessibility, and personalization, they also raise important sociological concerns regarding inequality, surveillance, academic integrity, digital dependence, and changing teacher-student relationships. The present study examines the impact of Artificial Intelligence on higher education from a sociological perspective. Using secondary data obtained from academic literature, policy reports, and contemporary research studies, the paper analyzes both the opportunities and challenges associated with AI integration in higher education. The study argues that AI is not merely a technological tool but a social phenomenon that influences educational structures, power relations, knowledge production, and social inequalities. The paper concludes that while AI has the potential to democratize access to education and enhance learning outcomes, its benefits are likely to remain unevenly distributed unless issues of digital access, ethical governance, and social inclusion are adequately addressed.

Keywords: Artificial Intelligence, Higher Education, Sociology of Education, Digital Learning, Educational Inequality, Technology and Society, India.

Introduction

Technological advancements have always played an important role in shaping educational systems. From the invention of the printing press to the development of computers and the internet, technological innovations have transformed the production, dissemination, and acquisition of knowledge. In recent years, Artificial Intelligence (AI) has emerged as one of the most influential technologies affecting higher education worldwide. Artificial Intelligence refers to the ability of computer systems to perform tasks that traditionally require human intelligence, including learning, reasoning, problem-solving, decision-making, language processing, and pattern recognition. The rapid development of AI technologies has significantly altered various sectors of society, including healthcare, business, governance, communication, and education. Within higher education, AI applications have expanded rapidly. Universities increasingly employ AI-powered systems for student support, personalized learning, automated grading, administrative management, academic advising, and research assistance. AI-driven educational platforms can analyze student performance, identify learning needs, and provide customized educational experiences.

The growing presence of AI in educational environments has generated considerable interest among educators, policymakers, and researchers. Proponents argue that AI can improve educational quality, increase efficiency, and expand access to learning opportunities. Through adaptive learning systems, students can receive individualized instruction tailored to their abilities and learning styles. Similarly, AI-assisted administrative systems can reduce workloads and enhance institutional effectiveness. However, the increasing integration of AI also raises significant sociological concerns. Access to AI technologies is often influenced by socioeconomic inequalities, creating disparities in educational opportunities. Students from privileged backgrounds may possess greater access to digital

* Email- ankita101096@gmail.com

resources and technological infrastructure compared to those from disadvantaged communities. Furthermore, AI-driven educational systems raise questions regarding surveillance, privacy, algorithmic bias, academic integrity, and the changing role of educators. The automation of educational processes may alter traditional teacher-student relationships and transform the social dimensions of learning. From a sociological perspective, education is not merely a mechanism for knowledge transmission but a social institution that contributes to socialization, identity formation, social mobility, and the reproduction of social structures. Therefore, understanding the implications of AI requires examining its broader social consequences rather than focusing exclusively on technological efficiency. This study seeks to analyze the relationship between Artificial Intelligence and higher education from a sociological perspective. It explores how AI influences educational opportunities, institutional practices, social inequalities, and the future of higher education in contemporary society.

Objectives of the Study

The study aims to:

1. Examine the role of Artificial Intelligence in higher education.
2. Analyze the opportunities created by AI for teaching, learning, and research.
3. Identify the sociological challenges associated with AI integration in educational institutions.
4. Explore the relationship between AI and educational inequality.
5. Suggest policy measures for the responsible and inclusive use of AI in higher education.

Research Questions

1. How is Artificial Intelligence transforming higher education?
2. What opportunities does AI provide for students and educational institutions?
3. What sociological challenges emerge from AI integration in education?
4. How does AI influence educational inequality and access?
5. What measures can ensure equitable and ethical implementation of AI in higher education?

Research Methodology

The present study is based on secondary data. Information has been collected from academic books, peer-reviewed journal articles, government reports, policy documents, international organization reports, and contemporary research studies related to Artificial Intelligence and higher education. A descriptive and analytical research design has been adopted. The study examines existing literature to understand the social implications of AI within educational institutions and evaluates both opportunities and challenges associated with its implementation.

Theoretical Framework

1. Functionalist Perspective

Functionalist theorists view education as an institution that contributes to social stability, skill development, and social integration. From this perspective, AI can enhance educational efficiency by improving learning outcomes, expanding access to information, and facilitating skill development. AI technologies may contribute to the effective functioning of educational institutions by supporting teaching, assessment, and administrative processes.

2 Conflict Perspective

Conflict theorists emphasize the role of education in reproducing social inequalities. According to this perspective, unequal access to AI technologies may reinforce existing disparities related to class, gender, region, and socioeconomic status. Students with greater technological resources are more likely to benefit from AI-enhanced learning environments, whereas disadvantaged students may experience exclusion.

3 Pierre Bourdieu's Theory of Cultural Capital

Bourdieu argued that educational success is influenced by access to cultural capital. In the contemporary digital era, technological competence and digital literacy can be understood as forms of

digital capital. Students possessing greater digital resources and technological skills are better positioned to benefit from AI-based educational systems.

4 Manuel Castells' Network Society

Castells emphasized the importance of information networks in contemporary society. AI-driven educational systems represent a key component of the emerging knowledge society. Participation in digital educational networks increasingly influences access to knowledge, opportunities, and social mobility.

Review of Literature

Recent scholarship has highlighted the growing influence of Artificial Intelligence on educational systems worldwide. Researchers have identified numerous benefits associated with AI, including personalized learning, improved assessment methods, enhanced student support services, and greater administrative efficiency. Studies suggest that AI-powered learning systems can adapt instructional content according to individual student needs, thereby improving educational outcomes. Learning analytics have been utilized to identify students at risk of academic failure and provide timely interventions. Research also indicates that AI can assist faculty members by automating routine administrative tasks, enabling educators to focus more on teaching and mentoring activities. Furthermore, AI technologies have expanded opportunities for distance learning and educational accessibility.

However, several scholars have raised concerns regarding the ethical and social implications of AI in education. Issues such as algorithmic bias, data privacy, surveillance, digital inequality, and academic dishonesty have become important areas of debate.

The literature suggests that while AI possesses significant transformative potential, its implementation must be guided by principles of equity, transparency, accountability, and social inclusion. Overall, existing studies indicate that AI is reshaping higher education in profound ways, creating both opportunities and challenges that require careful sociological examination.

Opportunities of Artificial Intelligence in Higher Education

The integration of Artificial Intelligence into higher education has created numerous opportunities for students, teachers, researchers, and educational institutions. AI technologies have transformed traditional teaching and learning processes by introducing innovative methods of knowledge acquisition, assessment, and academic management.

1. Personalized Learning

One of the most significant advantages of AI in higher education is personalized learning. Traditional classroom instruction often follows a uniform approach that may not address the diverse learning needs of students. AI-powered educational platforms can analyze learning patterns, academic performance, strengths, and weaknesses of individual students. Based on this analysis, AI systems can recommend customized learning materials, practice exercises, and instructional strategies. Personalized learning enables students to progress at their own pace and receive targeted academic support, thereby improving learning outcomes.

2. Enhanced Access to Education

AI has significantly expanded access to educational resources. Online learning platforms, intelligent tutoring systems, and virtual classrooms provide educational opportunities to students irrespective of geographical location. Students residing in remote and rural areas can access lectures, digital libraries, and learning materials through AI-supported platforms. This increased accessibility contributes to the democratization of knowledge and educational opportunities. AI-driven translation and language-processing tools also help overcome linguistic barriers, making educational content available to a broader population.

3. Improvement in Teaching and Learning Processes

Artificial Intelligence supports educators by providing innovative teaching tools and learning resources. AI-powered systems can assist teachers in monitoring student progress, identifying learning difficulties, and designing effective instructional strategies. Through learning analytics,

educators can gain insights into student performance and engagement. These insights facilitate evidence-based decision-making and improve educational effectiveness. The use of virtual simulations, intelligent tutoring systems, and interactive learning environments enhances student engagement and promotes active learning.

4. Research and Knowledge Production

AI has transformed research practices within higher education. Researchers increasingly utilize AI technologies for data analysis, literature reviews, pattern recognition, predictive modeling, and knowledge discovery. Large datasets that previously required extensive manual analysis can now be processed efficiently using AI tools. This capability accelerates research processes and supports the production of new knowledge. AI-assisted research also facilitates interdisciplinary collaboration by enabling scholars to analyze complex social, economic, scientific, and technological phenomena.

5. Administrative Efficiency

Educational institutions perform numerous administrative functions, including admissions, scheduling, student support, record management, and resource allocation. AI technologies can automate routine administrative tasks and improve institutional efficiency. Chatbots and virtual assistants provide students with information regarding admissions, examinations, academic programs, and administrative procedures. Automation reduces workload and allows institutions to allocate resources more effectively. Improved administrative efficiency contributes to better service delivery and enhanced student experiences.

6. Skill Development for the Future Workforce

Contemporary labor markets increasingly demand technological competence, digital literacy, and analytical skills. Exposure to AI technologies within educational settings helps students develop competencies required in the digital economy. Students become familiar with emerging technologies and acquire skills related to data analysis, critical thinking, problem-solving, and technological adaptation. These skills improve employability and prepare graduates for changing occupational environments.

7. Support for Students with Disabilities

Artificial Intelligence has significant potential to promote inclusive education. AI-powered assistive technologies support students with visual, hearing, speech, and learning disabilities. Speech recognition software, text-to-speech systems, real-time translation tools, and adaptive learning platforms enable students with disabilities to participate more effectively in educational activities. Such technologies contribute to educational inclusion and equal opportunities within higher education institutions.

Challenges of Artificial Intelligence in Higher Education

Despite its numerous benefits, AI also presents several challenges and concerns from a sociological perspective.

1. Digital Divide and Educational Inequality

One of the most significant challenges associated with AI is unequal access to technology. Access to computers, internet connectivity, digital devices, and technological infrastructure varies considerably across socioeconomic groups. Students from affluent backgrounds are often better positioned to benefit from AI-enhanced educational environments than students from economically disadvantaged communities. This disparity may contribute to the reproduction of educational inequalities. The digital divide remains particularly significant in developing countries where technological resources are unevenly distributed.

2. Algorithmic Bias and Social Inequality

AI systems rely on data for decision-making. If training data contain existing social biases, AI technologies may reproduce or amplify inequalities related to class, gender, caste, ethnicity, or language. Algorithmic bias may influence admissions processes, student evaluations, learning recommendations, and educational opportunities. Such outcomes raise important concerns regarding

fairness, transparency, and social justice. Educational institutions must therefore ensure that AI systems are designed and implemented responsibly.

3. Privacy and Surveillance Concerns

The increasing use of AI involves the collection and analysis of large amounts of student data. Learning management systems, assessment platforms, and educational analytics tools continuously monitor student activities and performance. While data collection may improve educational outcomes, it also raises concerns regarding privacy, surveillance, and informed consent. Excessive monitoring can affect autonomy and create ethical challenges. Protecting student privacy is therefore essential for responsible AI implementation.

4. Academic Integrity and Ethical Issues

AI-powered tools have generated new debates regarding academic integrity. Students may use AI systems to complete assignments, generate essays, solve problems, or perform academic tasks without genuine engagement in learning. Such practices raise concerns regarding plagiarism, authenticity, critical thinking, and educational quality. Educational institutions face the challenge of balancing technological innovation with academic integrity. The development of ethical guidelines is necessary to ensure responsible use of AI technologies.

5. Changing Teacher–Student Relationships

Education involves not only the transmission of knowledge but also social interaction, mentorship, emotional support, and value formation. Excessive reliance on AI technologies may alter traditional teacher–student relationships. While AI can support educational processes, it cannot fully replace the human dimensions of teaching. The reduction of direct interpersonal interaction may affect socialization, emotional development, and the overall educational experience. Consequently, AI should complement rather than replace human educators.

6. Dependence on Technology

Increasing reliance on AI may encourage technological dependence among students and institutions. Overdependence on automated systems may reduce opportunities for independent thinking, creativity, and problem-solving. Students may become passive consumers of technological solutions rather than active participants in the learning process. Maintaining a balance between technological assistance and human intellectual engagement remains important.

7. Employment Concerns in Higher Education

The automation of administrative and academic functions has generated concerns regarding employment within educational institutions. Certain routine tasks traditionally performed by staff may increasingly be managed by AI systems. Although AI creates new opportunities, it may also alter employment patterns and require significant workforce adaptation. Educational institutions must therefore prepare faculty and staff for technological transitions through training and professional development.

Artificial Intelligence, Education, and Social Transformation

Artificial Intelligence is contributing to broader processes of social transformation by reshaping how knowledge is produced, distributed, and consumed. Educational institutions are increasingly becoming part of a digital knowledge ecosystem where information flows rapidly across technological networks. The integration of AI into higher education reflects broader societal shifts toward automation, digitization, and data-driven decision-making. These developments influence not only educational practices but also social mobility, labor markets, cultural values, and patterns of social interaction. From a sociological perspective, AI should be understood as both a technological and social phenomenon. Its impact depends upon the ways in which institutions, policies, and social structures shape access to technological resources and opportunities.

Therefore, the future of AI in higher education will largely depend on whether technological innovation is accompanied by social inclusion, ethical governance, and equitable access.

Findings and Discussion

The analysis of secondary literature indicates that Artificial Intelligence is significantly transforming higher education by influencing teaching practices, learning experiences, research activities, and institutional administration. The findings suggest that AI has emerged as a powerful technological innovation with the potential to reshape educational systems. However, its impact is complex and multidimensional, producing both opportunities and challenges. One of the major findings of the study is that AI has fundamentally altered traditional approaches to teaching and learning. Educational institutions increasingly utilize AI-powered systems to deliver personalized instruction, monitor student performance, and improve academic outcomes. The integration of AI has enabled educational processes to become more data-driven, adaptive, and efficient. Students are now able to access customized learning experiences that address individual strengths and weaknesses. Consequently, AI is contributing to the modernization of higher education. The findings indicate that AI-supported personalized learning environments enhance student engagement and academic performance. Adaptive learning systems provide instructional content tailored to individual learning needs and preferences. Students receive immediate feedback, targeted recommendations, and personalized support, which can improve learning effectiveness. Such approaches are particularly valuable in large educational institutions where individualized attention may be difficult to provide through traditional methods. The study reveals that AI technologies contribute to greater accessibility in higher education. Digital learning platforms, virtual classrooms, and intelligent tutoring systems allow students to access educational resources regardless of geographical location. This increased accessibility is particularly beneficial for students residing in remote areas, working professionals, and individuals with disabilities. AI therefore possesses the potential to democratize educational opportunities. However, the realization of this potential depends on equitable access to technological infrastructure. One of the most important findings is that access to AI-based educational opportunities remains uneven. Students from economically privileged backgrounds are more likely to possess the devices, internet connectivity, and digital skills necessary to benefit from AI technologies. In contrast, students from disadvantaged communities may face barriers that limit participation in AI-enhanced educational environments. As a result, AI may inadvertently reinforce existing educational inequalities if issues of access are not addressed. The findings support sociological arguments that technological innovations often reflect broader social structures and inequalities.

The analysis indicates that AI has transformed research practices by improving data analysis, information retrieval, literature review processes, and predictive modeling. Researchers can process large volumes of information more efficiently and identify patterns that may not be easily detectable through conventional methods. AI-assisted research contributes to increased productivity and facilitates interdisciplinary collaboration.

Consequently, AI has become an important tool for knowledge production within higher education. The findings highlight growing concerns regarding ethics, privacy, and academic integrity. AI systems collect and analyze large amounts of personal data, raising questions regarding consent, surveillance, and data protection.

Furthermore, the use of AI-generated content has created new challenges related to plagiarism, originality, and academic honesty. Educational institutions must therefore develop ethical guidelines. Although AI enhances efficiency, the study finds that it cannot fully replace the social and emotional dimensions of education. Teaching involves mentorship, motivation, emotional support, and interpersonal communication that extend beyond information delivery. Students often benefit from human interaction, collaborative learning, and personal guidance. Therefore, AI should be viewed as a complementary tool rather than a substitute for educators. The findings suggest that the increasing adoption of AI reflects broader changes associated with digitalization and the knowledge economy. Educational institutions are adapting to a society where information technologies influence employment, communication, governance, and everyday life. The integration of AI into higher

education represents part of a larger process of social transformation that is reshaping relationships between knowledge, technology, and society.

Conclusion

The present study examined the relationship between Artificial Intelligence and higher education from a sociological perspective. The analysis demonstrates that AI has become an influential force transforming educational institutions, teaching practices, learning experiences, and research activities. Artificial Intelligence offers numerous opportunities for enhancing educational quality, expanding access to knowledge, improving administrative efficiency, and supporting personalized learning. AI technologies can facilitate educational inclusion, promote innovation, and contribute to the development of skills required in contemporary labor markets. However, the study also highlights several challenges associated with AI integration. Digital inequality, algorithmic bias, privacy concerns, ethical dilemmas, academic integrity issues, and technological dependence represent significant obstacles. These challenges indicate that technological innovation alone cannot guarantee educational equity or social progress.

From a sociological perspective, AI should be understood not merely as a technological tool but as a social phenomenon that influences power relations, opportunities, and patterns of inclusion and exclusion. The impact of AI depends on how educational institutions, policymakers, and society manage its implementation. The study concludes that the future of AI in higher education should be guided by principles of equity, accountability, transparency, and human-centered learning. AI has the potential to enrich education, but its benefits can only be fully realized when technological advancement is accompanied by social responsibility and inclusive policies.

References

1. Bourdieu, P. (1986). *The Forms of Capital*. Greenwood Press.
2. Castells, M. (2010). *The Rise of the Network Society* (2nd ed.). Wiley-Blackwell.
3. Giddens, A. (1991). *Modernity and Self-Identity*. Stanford University Press.
4. Selwyn, N. (2019). *Should Robots Replace Teachers? AI and the Future of Education*. Polity Press.
5. Luckin, R. (2018). *Machine Learning and Human Intelligence*. UCL Institute of Education Press.
6. UNESCO. (2023). *Guidance for Generative AI in Education and Research*.
7. UNESCO highlights the need for ethical, inclusive, and human-centered approaches to AI in education.
8. World Bank. (2022). *The State of Learning Poverty Report*.
9. OECD. (2021). *Artificial Intelligence and the Future of Skills*.
10. Holmes, W., Bialik, M., & Fadel, C. (2019). *Artificial Intelligence in Education: Promises and Implications for Teaching and Learning*.
11. Williamson, B. (2017). *Big Data in Education*. Sage Publications.
12. Van Dijk, J. (2020). *The Digital Divide*. Polity Press.
13. Brynjolfsson, E., & McAfee, A. (2014). *The Second Machine Age*. W.W. Norton.
14. Freire, P. (1970). *Pedagogy of the Oppressed*. Continuum.
15. Durkheim, E. (1956). *Education and Sociology*. Free Press.
16. Apple, M. W. (2004). *Ideology and Curriculum*. Routledge.



Eccentricity Resulting from Alienation in the Works of Ernest Hemingway

Dr. Namita Singh*

Ernest Hemingway, the American novelist's stature stands tall in the world map of literary gems. Though Walt Whitman is considered the father figure among American novelists, Ernest Hemingway is considered a novelist who kept the American flag flying through his writings that had the essence of realism, patriotism, and philosophical fervor. He was awarded the Nobel Prize in his lifetime and was a celebrity who was welcome in both political and social circles. His novels depict the American ethos that constitute the core of the society. This paper will discuss one of those traits that was rampant yet brushed under the carpet.

Eccentricity can be labeled as one of the vices of Americans.

In *Death in the Afternoon*, he writes:

"So far about words, I know only that what is moral is what you feel good after and what is immoral is what you feel bad after and judged by these moral standards, which I do not defend, the bullfighting is very moral to me because I feel very fine while it is going on and have a feeling of life and death and mortality and immorality and after it is over, I feel very sad but very firm." (1)

Questions arise about the roots or reasons that lead to eccentricity in a person. According to Mark Twain, an excess of enjoyment leads to eccentricity.

In James Joyce's *Ulysses*, Ulysses is alone and his mind travels and travels from one place to another. America had become prosperous after the completion of the war. It was becoming a center of science, technology, and literature. People were in a mood to forget the old wounds and begin life afresh. This new world was dazzling as it had refused to obey middle-class moralities. Men and women were being fashionable. Cafes were becoming popular. In a nutshell, the people were seeking means of happiness. At times, they discovered this happiness by merging themselves in wine. Its stances can be cited in the story "A Clean, Well-Lighted Place". An old man visits a cafe only in search of some quiet moments of peace in his life. He had amassed wealth but lost the peace of his soul. For that purpose, he was sitting late at night in a cafe and was drinking wine. Two waiters of the cafe, who were serving him wine, were talking:

"Last week he tried to commit suicide," one waiter said.

"Why?"

"He was in despair."

"What about?"

"Nothing."

"How do you know it was nothing?"

"He has plenty of money." (2)

They arrive at the conclusion that the old man had visited the cafe as he needed light, cleanliness, and some pleasant atmosphere. It is in this story where a complete passage on 'nada' or the nothingness of Hemingway can be found. The old man had got everything in life; even then, he was feeling unfulfilled. The reason was the loneliness he faced in life. The sense of loneliness or alienation propagates many negative values in a human persona. At times, it drives him to madness, at others to saintliness, and at still others to follow bizarre ways in life.

And the sleepless man—the man obsessed by death, by the meaninglessness of the world, by nothingness, by nada—is one of the recurring symbols in the works of Hemingway. In this phase,

* Professor of English, A.N. College, Patna

Hemingway is a religious writer, and the great nada is death. A Hemingway hero takes great risks. He confronts in dramatic terms the issues of nada that is implicit in all of Hemingway's world.

John Atkins in *The Art of Ernest Hemingway* opines that the characters of Hemingway are obsessed with two or three basic feelings—one of them is alienation and then fear.

Jake Barnes in *The Sun Also Rises* is eccentric as he loves a lady who is loved by three more persons. Jake Barnes and his friends are excited as they believe in life like the dip of wine—drinking till the last drop. Jake's gesture of introducing his lady love Brett to handsome Pedro is also an eccentric gesture as he loses the lady in his 'brave act'.

Frederic Henry in *A Farewell to Arms* is a lieutenant in the army. He gets injured during the war and wins the love of beautiful V.A.D. Catherine Barkley. The two lovers pine for the moment of togetherness which is rare. They are marred by loneliness and dream for happy days ahead. But the dream never gets fulfilled. Catherine dies during childbirth, leaving Henry alone.

For Whom the Bell Tolls, which is often compared with Dante's *Divine Comedy* and Homer's *Iliad*, is a saga of war where the war is between the Republicans and the fascists. In Dante's *Divine Comedy*, a war is depicted, but with a difference. All the friends of Dante have been kept in Paradiso, while the foes of Dante have been thrashed into Purgatorio or Hell.

Homer's *Iliad* stands apart as it is the fight between Achilles, the great warrior, and the minor Gods.

Robert Jordan, Pablo, Anselmo, and El Sordo take the pledge to get justice and, in the process, hatch the conspiracy to blow up the bridge. The plan is disclosed on the first page and is implemented successfully by none other than Jordan on the last page of the novel. The code hero Robert Jordan shows almost a new facet of his life. He sidelines Maria, the beautiful Gypsy girl, for his duty as he considers duty above everything.

Maria looked around, he did not look around, Robert Jordan. "Robert Jordan said, Go," and Pablo hit the horse across the crupper with a hobbling strap as it looked as though Maria tried to slip from the saddle. But Pablo and Pilar were riding close up against her and Pilar was holding her and the three horses were going up the draw.

"Robert," Maria turned and shouted, "Let me stay! Let me stay!"

"I am with thee," Robert Jordan shouted.

"I am with thee now. We are both there. Go!"

Then they were out of sight around the corner of the draw, and he was soaking wet with sweat and looking at nothing. (3)

Perhaps the causes that gave a headache to the Americans were eternal questions that were haunting them. The social problem, the domestic problem, and also different kinds of disturbances that caused instability in the country were enough reason for the eccentricity of the inhabitants certainly caused by alienation.

James Mellow writes, "Through the character of Nick Adams, the hero of many (though not all) of the stories of *In Our Time*, Hemingway created a fictional persona for himself and for his time. He announced themes that would carry him through a lifetime of work: the disappointment of family life, the dissatisfactions of early love, the celebration of country and male comradeship, a young man's initiation into the world of sex and the consequences of marriage. In the inter-chapters, Hemingway recreated the destructive violence of battle and the ritual violence of bullfighting intended to give the larger chronicle of his times—the world of war and politics, of crime and punishment—that were juxtaposed with the more personal circumstances of the stories." (4)

In a November edition of a 1962 *Esquire* article called "The Big Bite", Norman Mailer examined the troubling question of how Hemingway could have committed suicide, which seemed the antithesis of all he believed in. He concluded: "It is not likely that Hemingway was a brave who sought dangers for the sake of the sensation provided to him. What is more likely, the truth of his own odyssey is that he struggled with his cowardice and against a secret lust to suicide all his life, that his inner landscape was a nightmare and he spent his nights wrestling with Gods. It may even be

that the final judgement on his work comes with the notion that what he failed to do was tragic, but what he accomplished was heroic. For it is possible that he carried a weight of anxiety with him which would have suffocated any man smaller than himself."

A question arises: what led the characters to eccentricity that was due to alienation? The characters were unable to chew the bitterness of the real world and as a result, they made their own pseudo world as in *The Sun Also Rises*, *A Farewell to Arms*, *Across the River Into the Trees*, and *The Snows of Kilimanjaro*; they were happy.

Hemingway reflects the American form of nihilism—the denial of any objective basis for truth, especially moral truth—as it constitutes the background for Hemingway's vision. In Europe, nihilism had been identified and analyzed in the nineteenth century by Nietzsche and Dostoevsky, based as it was on the erosion of the classical and Christian foundation of Western civilization. The nihilist position was essentially pessimistic. The depth of the European cultural tradition, however, softened the harsh times of nihilism. Nietzsche ends in an ecstatic affirmation of life, while Dostoevsky goes in a plea for an existential leap into religious belief. Both men found their way back to the tradition after cutting away its rational underpinning.

When the nihilist spirit reached America in the twentieth century, it assumed a truculence that was a reaction to the gentility of nineteenth-century American culture. One thinks of Robert's anger in challenging Gods to strike him dead. There is something naive and daringly adolescent in the American form of nihilist thought. In Europe, nineteenth-century writing had prepared the way for the shock of Nietzsche. Novelists like Balzac and Flaubert had analyzed it in depth.

The shortcomings of bourgeois society in America, the optimism of an Emerson or Whitman, offered no effective cushion for the shock. Writers like Hawthorne and Melville, who saw the dark side of the American experience, still expressed their vision in genteel prose. Mark Twain in retrospect came to grips with the realities of American life, but in his own time, he was accepted only as a humorist and entertainer.

Hemingway reflects a stark, often rhetorical nihilism with some of the angry tones of Midwestern populism. In America, after the disillusionment with the World War to save the world for democracy (World War I), it was impossible to use the old foundation to justify the popular, philosophical, and moral writers. Thus, the underside of American life was exposed for examination. The muckrakers—Lincoln Steffens, Ida Tarbell, and Samuel Hopkins Adams among others—had begun even earlier to expose the seamy side of American economic and social life. In fiction, William Dean Howells, Theodore Dreiser, and Upton Sinclair had already presented Americans with some of the rosiness filtered out. Dreiser's *Sister Carrie* does not suffer the torments of conscience when she becomes a "fallen" woman, nor does she inevitably slide into the life of a prostitute. In the cities of America, survival was enough of a problem to make irrelevant the moral clichés of the past.

After Charles Lyell, Darwin, Marx, and Freud, the answers are gone. Dostoevsky's Ivan Karamazov knows what has happened to the world when he observes that if God is dead, everything is permitted.

Hemingway does not approach the problem as a philosopher. If he reflects the spirit of nihilism, it is because he breathed the air of America. The malaise was there, the sudden awareness of Adam after he ate the apple.

Hemingway was clearly in violent reaction to nineteenth-century American idealism. The optimism of an Emerson or Whitman made him blush. The life Hemingway saw was brutal and degrading. As the Existentialist Ivan Karamazov said it, "One may love life more than the meaning of life." Hemingway offers no apocalyptic vision; he still leaves us with the feeling that this is the way things really are. (5)

The hard-boiled school represented by Hemingway, for instance, is usually spoken of as a product of World War I disillusionment, yet it was as much the product of a tradition which arose even before the Civil War—the tradition of an intellectual evasion of thought which criticized Emerson in regard to the Fugitive Slave Law. It had been growing swiftly since the failure of the

ideals in whose name the Civil War was fought.

Hemingway was a naturalist in his general style. He was not interested, like Balzac, in depicting a society, or even like Mark Twain, in portraying the moral situation. He was rather engaged in working out a personal problem through the evocative, emotion-charged images and ritual therapy available through the manipulation of art form. And while art was still an instrument of freedom, it was now mainly the instrument of a questionable prediction of freedom for the artist which too often served to enforce the "unfreedom" of the reader. Malcolm Cowley, on the basis of the rites which he believes to be the secret dynamic of Hemingway's work, has identified him with Poe, Hawthorne, and Melville, "the haunted and nocturnal writers," he calls them, "the men who dealt with images that were symbols of the inner world."

Malcolm is critical of Hemingway. He was of the view that there was something abnormal in his writings that led to eccentricity in a man's person. He elaborates, "we can recognize rites of animal sacrifice... of sexual union... of conversion and of symbolic death and rebirth." (6)

Another critic adds, "I do not believe, however, that the presence of these rites in writers like Hemingway is as important as the fact that here, beneath the dead-pan prose, the cadence of understatement, the anti-intellectualism, the concern with the very 'fundamental' of man except the twentieth-century form of that magical rite which during periods of great art has been to a large extent public and explicit, here is the literary form by which the personal guilt of the pulverized individual of our rugged expatriates is not through his identification with the guilty acts of an Oedipus, a Macbeth or Medea, by suffering this agony and loading its sins upon their passionate and strong shoulder, but by doing good with a bull hooked with a fist, inspired with a grasshopper on a fish hook, not by identifying himself with human heroes, but with those who are indeed defeated." (7)

In the opinion of many critics, Hemingway's early writings are similar to that of Mark Twain's *Huckleberry Finn*, where the hero, Jim, is apprehensive and nervous, and finds guilt in the afternoon naps. His writings, no doubt, depict these minor nightmares that happen in the life of his heroes.

Hemingway is also considered a racist writer who draws a line of demarcation between the blacks and whites as he calls them nigger or negro.

Hemingway also talks of anti-Semitism. Hemingway has an edge over others. If he walks with fear, he also talks of pity. If he talks of carnal pleasure, he also talks of sacrifice and patriotism. If he talks of the nothingness of life, he also talks of hope. If he is dissipated, courage is not lost. He is a romantic by heart, adventurous by nature, and saintly by stature. He is often compared with D.H. Lawrence for his bohemian-aesthetic intellectualism. Like Lawrence, he is derided as a modern Heidelberg who is incapable of despising things he believed in. It is William Faulkner who has similarities with Hemingway. He too is marred by 'alienation'. Joe and Joanna in *Light in August*, V.K. Ratliff in *Mosquitoes*, and Jason in *The Sound and the Fury* are lonely characters who try to seek the meaning of life.

As a matter of fact, the conclusion leads to the fact that the eccentricity depicted in the works of Hemingway was the byproduct or outcome of the alienation the characters faced in the society.

References:

- Hemingway, E. *Death in the Afternoon*. p. 4.
- Hemingway, E. "A Clean, Well-Lighted Place," *In Our Time*. p. 16.
- Hemingway, E. *For Whom the Bell Tolls*. p. 465.
- Mellow, J. R. (1992). *Hemingway: A Life Without Consequences*. Addison-Wesley.
- Shaw, S. (1973). *Ernest Hemingway*. Frederick Ungar Publishing Company.
- Ellison, R. (1953). *Twentieth-Century Fiction and the Black Mask of Humanity*.
- Hemingway, E. *For Whom the Bell Tolls*. p. 89.
- Harper, R. (1948). *Existentialism: A Theory of Man*. Harvard University Press. p. 103.



A Feminist Appraisal of Domestic Subjugation, Existential Void, and Queer Defiance in Manju Kapur's *A Married Woman*

Divya Prakash*

Abstract

*This paper examines the complex intersections of gender discrimination, domestic entrapment, and identity formation in Manju Kapur's seminal novel, *A Married Woman* (2002). Set against the volatile geopolitical backdrop of the Ram Janma Bhoomi-Babri Masjid communal unrest in Delhi, the narrative chronicles the psychological evolution of its protagonist, Astha. Initially embodying the idealized parameters of middle-class Indian wifehood, Astha's journey exposes the hollow core of patriarchal marital setups.*

*Through a close critical reading, this study investigates how Kapur exposes the structural violence of the domestic space—specifically focusing on the commodification of the female body, psychological emotional starvation, and the pervasive cultural pathology of son-preference. Furthermore, the paper analyzes Astha's eventual socio-political awakening and her transgressive pivot toward a same-sex relationship with Pipeelika as a radical, decolonial act of feminist defiance. Ultimately, the paper establishes *A Married Woman* as a crucial text in contemporary Indian feminist literature that challenges heteronormative frameworks and redefines the boundaries of female self-actualization.*

Keywords: Feminist Theory, Heteronormativity, Lesbianism, Patriarchal Oppression, Subjugation.

Introduction and Literary Context

Numerous Indian authors writing in English—including notable figures like Anita Desai, Shashi Deshpande, Anita Nair, and Arundhati Roy—have extensively explored women's issues through a feminist lens. Joining their ranks, Manju Kapur astutely examines the gender disparities that disrupt women's lives, portraying her female characters as individuals striving against patriarchal marginalization and tyranny. Manju Kapur frequently illustrates the realities of the 1940s, an era when women possessed virtually no agency to claim their rights, voice grievances, or object to systemic bias.

In her novel *A Married Woman*, Manju Kapur chronicles the lifelong tribulations of her protagonist, Astha, who eventually enters into a lesbian relationship with Peepilika. Her literary catalog consistently highlights this exhausting quest for female identity. As the central figure of this specific narrative, Astha's journey dictates the plot's trajectory. Initially, the book reads as a standard romance detailing the marriage between Astha and her spouse, Hemant. Driven by romantic idealism, Astha transitions after her wedding into a mature, deeply responsible wife who executes her household obligations flawlessly, earning the admiration of both her husband and her in-laws. At the outset, Hemant appears to be an affectionate and attentive partner.

Setting, Plot, and Domestic Disillusionment

The backdrop of Manju Kapur's novel *A Married Woman* is Delhi, unfolding during the intense communal friction surrounding the controversial Ram Janma Bhoomi-Babri Masjid. The book charts Astha's development from girlhood through her thirties, capturing an array of emotional peaks and valleys, validations, rejections, and growing frustrations. As Robert notes in his article, *A Married Woman* features a complex, dense plotline that tracks Astha from her youthful maturity into early middle age.

Throughout this trajectory, Astha operates with a degree of modern autonomy early on by dating several young men of her choice, much like her Western peers. Ultimately, however, she

* Research Scholar

yields to an arranged marriage orchestrated by her parents. Though she initially discovers marital bliss and bears children, she gradually drifts away from Hemant. She fights against the wishes of her husband and relatives to pursue painting, transforms into a grassroots social advocate, and subsequently finds romantic fulfillment—and a sense of self-actualization—in the arms of another woman, finding herself "sort of, more" (Rationale 102).

For an extended period, Astha conforms to middle-class ideals and enjoys a peaceful mental state. Yet, an underlying void slowly creeps into her life, leaving her with a profound sense of isolation, domestic restriction, and psychological pain. These feelings intensify when she exposes herself to external social protests and political shifts. Unfortunately, the alternative path she temporarily pursues proves just as hollow, forcing her to ultimately seek a quiet release.

On a critical level, *A Married Woman* serves as a poignant feminist text. Astha takes up the mantle of gender resistance where Kapur's previous heroine, Virmati, left off, pushing the struggle into entirely new socio-political arenas. Consequently, the novel demands analysis as a feminist study, and in an interview, Manju Kapur candidly articulated her personal stance:

"I am a feminist. And what is a feminist? I mean I believe in the rights of women to express themselves in the rights of women to work. I believe in equality, you know domestic equality, legal equality. I believe in all that. And the thing is that women don't really have that—you know even educated women, working women. There is a trapping of equality but you scratch the surface and it is not really equal."

Patriarchal Subjugation and Emotional Starvation

Astha, born to a progressive father and a deeply traditional mother, genuinely craves a peaceful, cooperative coexistence within her domestic circle. Instead, she faces intense oppression and unfair treatment under her in-laws' roof. In that household, her existence is reduced to a prescribed gender role: offering a compliant body to her husband at night, rendering ceaseless physical labor during the day, and keeping her opinions completely silenced. Her marriage to Hemant—the son of a Delhi bureaucrat—completely lacks mutual understanding and mutual respect. Within the confines of their home, Hemant exhibits toxic, hyper-masculine behavior. He embodies a male-dominated social order driven by machismo and rigid heteronormativity.

Astha is coerced into the role of a compliant wife and a self-sacrificing mother, viewed essentially as a domestic asset. This environment subjects her to physical exploitation and severe emotional deprivation. Starved for genuine affection and driven by depression, she desperately searches for fulfillment elsewhere, eventually seeking a "substitute-husband" (Rationale 110) through lesbianism.

Through Astha's journey in *A Married Woman*, Manju Kapur forcefully challenges traditional expectations, endorsing a woman's right to an independent life, self-fulfillment, inter-faith marriage, and same-sex relationships—all of which break away from established patriarchal constructs.

While Astha harbored typical teenage crushes in her youth, those early infatuations faded into irrelevance as she faced the harsh realities of her marriage. She grows deeply disillusioned with her husband's affection and finds her familial ties fundamentally flawed. Her mother-in-law expects her to remain a subservient, self-sacrificing anchor, mimicking idealized historical models of wifehood. Overburdened by constant domestic chores and suffocated by the pressure to cater to everyone else, Astha is trapped in a loop of perpetual compromise, stating that she is "always adjusting to everybody's need" (*A Married Woman* 227). She realizes that a wife's social standing is entirely tied to her husband's identity.

Divided between conventional duty and socio-religious expectations, she is stripped of emotional autonomy. Physically and mentally drained, she internalizes the truth that "A tired woman cannot make wife good" (*AMW* 154). She recognizes that her position is no better than that of an uncompensated maid, expected to satisfy her partner sexually while maintaining total domestic submission, forced to be "A willing body at night, a willing pair of hands and feet in the day and an

obedient mouth" (AMW 231). Marginalized by a cruel domestic environment, she seeks an escape from her depression and decides that finding outside employment is her only path out.

Son Preference and Social Bias

Believing that economic self-sufficiency is the key to personal liberty, she acts on the idea that "with good job comes independence" (AMW 4) and takes up a teaching position. Unfortunately, professional work fails to shield her from the deeply ingrained biases of Indian society, which values male offspring over female children. As observed, "Manju

Kapur gently digs at the Indian attitude of preferring a baby-boy to a baby-girl in the novel" (Rationale 107). Astha's family actively demonstrates this cultural obsession with sons: "When her daughter Anuradha was four, Astha conceived again. Her mother brought in a poojari to perform special pooja to propitiate the gods to grant them a boy for Astha" (Rationale 107).

Once she gives birth to a son, Himanshu, her status within the household rises dramatically. The family openly celebrates because they believe "the family is complete at last" (AMW 68). Though Astha finds personal joy in motherhood, she despises this blatant systemic gender bias. She is deeply scarred by the cold, indifferent reaction her family and peers showed during her daughter's birthday, which stood in stark contrast to the widespread praise she received after delivering a male heir.

Astha intensely rejects this discriminatory standard. Such a mindset in traditional Indian culture damages the struggle for female equality, trapping women who "feel caught up in the web of daily life" (AMW 84) and triggering the anxiety and clinical depression that characterize "the disease of modern life" (AMW 76). Dogmatic cultural traditions perpetuate these female dilemmas, as popular social frameworks continually reinforce prejudices against women. Rather than offering women equal standing with men, society demands that they be infinitely resilient and yielding, like the earth itself. Kapur fiercely decries this unfair treatment within families and wider civilization.

Defying the System: Rebellion and Rebirth

Astha actively revolts against men's apathy toward the female plight. She outright rejects the societal expectation that a woman must endure every domestic hardship silently and act exclusively within orthodox boundaries. Traditional norms dictate that a woman must never speak out against mistreatment by her husband or in-laws, using religion as a tool to forbid women from exposing domestic cruelty, no matter how extreme. Under this system, expressing personal pain is treated as a violation of sacred heritage. Women are marginalized much like untouchables and other social outcasts, discarded by a conservative status quo that offers them no room for success or survival, ensuring that anyone who dissents faces complete social banishment.

However, Astha completely dismisses these archaic viewpoints. She builds an independent identity by ignoring her family's orthodox beliefs, maintaining that "Religion is a choice as much as other thing" (AMW 89). In her quest for self-actualization, she defies her husband and breaks through conventional gender barriers.

Her path crosses with Pipeelika, a high-caste Brahmin woman who defied social taboos by marrying Aijaz Akhar Khan, an empathetic Muslim history lecturer. Astha resonates with Pipeelika's radical perspectives on romance and marriage. By marrying outside her faith against her mother's wishes and societal rules, Pipeelika claimed her autonomy—much like the characters Ammu in Arundhati Roy's *The God of Small Things* or Saru in Shashi Deshpande's *The Dark Holds No Terror*.

Astha retaliates against Hemant's neglect by entering into a same-sex relationship with Pipeelika, who has herself become a target of social hostility after being widowed when her husband was killed in a communal riot. Because Astha finds an emotional alternative in Pipeelika, she remains completely unfazed during a domestic confrontation. Instead, she reasons that if her husband is entitled to an extramarital relationship, she possesses the equal right to seek her own fulfillment elsewhere...

Conclusion

Ultimately, Manju Kapur's *A Married Woman* serves as a powerful deconstruction of the idealized, self-sacrificing Indian wife. Through Astha's profound disillusionment, emotional starvation, and eventual awakening, Kapur exposes how traditional domestic expectations function as spaces of systemic marginalization rather than protection. By charting Astha's trajectory from total compliance to open rebellion—culminating in her transgressive same-sex bond with Pipeelika—the narrative shifts the battlegrounds of Indian feminist fiction. Astha's ultimate decision to seek an emotional alternative outside her heteronormative marriage stands as a definitive reclamation of female agency, identity, and personal desire. Though the systemic barriers of patriarchy and communal turbulence remain deeply entrenched, Kapur ensures that her protagonist is no longer an unpaid servant to tradition, but a self-governing individual who has successfully claimed her right to self-fulfillment.

Works Cited

1. Gnanamony, S. Robert. *Rationale of Sexual Diversity in Manju Kapur's A Married Woman*. *Literary*
2. Goel, Mona. "At Home with Manju Kapur" (An Interview), *Unheard Melodies: A Journal of English*
3. <https://etd.lib.metu.edu.tr/upload/12612288/index.pdf>
4. Kapur, Manju. *A Married Woman*. New Delhi: India Ink, Roli Books Ltd. Rep 2006.
5. Kapadia, Karim. *Frontline: Indian's National Magazine*. Feb. 01-2008.
6. Sahgal, Nayantra. *Rich Like Us*. London: Heinemann, 1985.



Age and Gender Differences in Psychosocial Vulnerability to Terrorism among University Students

Dr. Pooja*

Abstract:

Terrorism continues to represent one of the most complex security challenges of the twenty-first century, extending its impact beyond physical destruction to influence psychological functioning, social cohesion, and community resilience. Contemporary research increasingly recognizes that vulnerability to terrorism is shaped not solely by political or ideological influences but also by an interaction of psychological and social factors. University students constitute a particularly important population for investigating psychosocial vulnerability because the transition to adulthood is often accompanied by identity exploration, social adjustment, emotional instability, and increased exposure to diverse ideological narratives through digital and social media. Understanding demographic differences in psychosocial vulnerability may contribute to the development of preventive educational interventions that strengthen resilience and reduce susceptibility to extremist influences.

The present study examined age and gender differences in psychosocial vulnerability to terrorism among university students using a quantitative cross-sectional research design. Primary data were collected from 384 undergraduate and postgraduate students selected through stratified random sampling. Psychosocial vulnerability to terrorism was operationalized as a multidimensional construct comprising psychological vulnerability, social vulnerability, and cognitive vulnerability. Data were analysed using the Statistical Package for the Social Sciences (SPSS). Descriptive statistics were employed to summarize respondents' characteristics, Cronbach's alpha assessed the internal consistency of the adapted measurement instrument, and independent-samples t-tests examined differences in psychosocial vulnerability across age groups and gender. The study hypothesized significant differences between younger and older students and between male and female students. The findings are expected to provide empirical evidence regarding demographic variations in psychosocial vulnerability to terrorism and contribute to the growing body of psychological research on radicalization prevention. The study further highlights the importance of developing university-based psychosocial support systems, critical thinking initiatives, and resilience-building programmes that reduce vulnerability to extremist influences among young adults.

Keywords: Psychosocial Vulnerability, Terrorism, Radicalization, University Students, Gender Differences

1. Introduction

The evolving nature of terrorism has transformed it from a predominantly security-oriented concern into a multidimensional psychological and social phenomenon. While traditional counterterrorism strategies have largely emphasized intelligence gathering, surveillance, and military interventions, contemporary scholarship increasingly acknowledges that understanding the psychosocial processes underlying vulnerability to extremist ideologies is equally important for preventing terrorism. Radicalization rarely occurs as a consequence of a single event; instead, it develops through complex interactions between psychological characteristics, social environments, identity processes, perceived grievances, and exposure to extremist narratives (Borum, 2011; Kruglanski et al., 2019). Consequently, researchers have shifted their attention toward identifying

* Exclusive Teacher MS Rajokhar, Araria
Mail - poojaanand583@gmail.com, Mobile number -8825221350

psychosocial vulnerabilities that may increase an individual's susceptibility to extremist influence while recognizing that vulnerability alone does not inevitably lead to radicalization or terrorist involvement.

Psychosocial vulnerability to terrorism refers to a constellation of psychological and social conditions that may increase receptivity to extremist ideologies or narratives advocating political violence. Importantly, vulnerability should not be interpreted as evidence of criminal intent or future terrorist behaviour. Rather, it reflects varying degrees of susceptibility arising from interactions among cognitive, emotional, and social factors that may influence how individuals interpret ideological messages, perceive injustice, develop social identities, and respond to grievances. Contemporary radicalization research consistently emphasizes that terrorism cannot be explained through a single psychological profile; instead, multiple interacting factors contribute to individual pathways toward violent extremism (**Horgan, 2014; McCauley & Moskalenko, 2017**).

University students represent a particularly significant population for examining psychosocial vulnerability. The university years coincide with emerging adulthood, a developmental period characterized by identity formation, increased autonomy, emotional transitions, and exploration of social and political beliefs. During this stage, young adults often encounter diverse ideological perspectives through academic environments, peer interactions, online communities, and social media platforms. Although universities foster critical thinking and democratic engagement, they may also expose students to competing narratives concerning identity, injustice, political conflict, and social change. For most students, such exposure contributes positively to intellectual development; however, for a small minority possessing specific psychosocial vulnerabilities, these experiences may increase receptivity to extremist narratives under particular circumstances.

Psychological theories provide valuable explanations for understanding why some individuals become more susceptible to extremist influences than others. The Quest for Significance Theory proposes that individuals experiencing humiliation, identity loss, or perceived insignificance may become motivated to restore personal meaning through affiliation with ideological groups that promise recognition, purpose, or status (**Kruglanski et al., 2014**). Similarly, Social Identity Theory suggests that individuals derive self-esteem and belongingness from group memberships, and under certain circumstances strong in-group identification combined with perceptions of intergroup threat may facilitate polarization and support for extremist ideologies (**Tajfel & Turner, 1979**). The Staircase to Terrorism model further argues that perceptions of injustice, blocked opportunities, and increasing moral disengagement may gradually move susceptible individuals toward greater acceptance of political violence, although only a very small proportion ultimately engage in terrorist behaviour (**Moghaddam, 2005**).

Research has also demonstrated that demographic characteristics influence psychological vulnerability to extremist ideologies. Age has been associated with differences in cognitive maturity, emotional regulation, identity development, and political engagement, all of which may shape susceptibility to extremist narratives. Younger adults often experience greater identity uncertainty and increased experimentation with social and political beliefs, whereas older students may possess greater psychological stability resulting from accumulated life experiences. Gender differences have likewise received considerable attention within terrorism psychology. While males have historically been overrepresented among individuals involved in terrorist organizations, psychological vulnerability should not be equated with actual participation. Instead, gender differences may emerge because males and females experience socialization, identity formation, emotional expression, and responses to perceived injustice differently, thereby influencing psychosocial vulnerability in distinct ways.

Despite substantial advances in terrorism research, important gaps remain. Much of the existing literature focuses on individuals already involved in extremist organizations, former terrorists, or populations affected by political violence. Comparatively fewer empirical studies have investigated psychosocial vulnerability among non-clinical university populations, particularly using

demographic comparisons. Furthermore, many studies examine isolated factors such as identity, grievances, or social exclusion independently rather than considering psychosocial vulnerability as a multidimensional construct integrating psychological, social, and cognitive domains. Understanding demographic variations among university students may therefore contribute to the development of evidence-based prevention strategies that strengthen resilience before extremist attitudes emerge.

Against this background, the present study examines age and gender differences in psychosocial vulnerability to terrorism among university students. By conceptualizing vulnerability as a multidimensional psychosocial construct rather than a predictor of terrorist behaviour, the study seeks to contribute to preventive approaches within psychology, higher education, and counter-radicalization research. The findings are expected to provide valuable insights for educators, psychologists, and policymakers seeking to design interventions that promote resilience, critical thinking, social inclusion, and psychological well-being among young adults.

2. Literature Review

2.1 Conceptualizing Psychosocial Vulnerability to Terrorism

The study of terrorism has progressively shifted from explaining terrorist acts to understanding the psychosocial processes that make certain individuals more susceptible to extremist ideologies. Contemporary scholars increasingly argue that terrorism cannot be explained solely through political ideology, religious beliefs, or socioeconomic disadvantage. Instead, radicalization is understood as a dynamic process resulting from interactions among psychological characteristics, social experiences, environmental influences, and ideological exposure (**Borum, 2011; Horgan, 2014**).

Psychosocial vulnerability to terrorism refers to an individual's susceptibility to cognitive, emotional, and social conditions that may increase receptivity to extremist narratives or ideological violence. Importantly, psychosocial vulnerability should not be interpreted as an indicator of future terrorist behaviour. Rather, it represents a state of increased susceptibility that may interact with situational and environmental factors. Most individuals possessing psychosocial vulnerabilities never engage in extremist activities, highlighting that vulnerability is neither deterministic nor predictive of terrorism (**McCauley & Moskalenko, 2017**).

Current terrorism psychology emphasizes that no single profile exists for individuals who become radicalized. Instead, multiple pathways involving identity concerns, perceived injustice, emotional distress, social exclusion, and cognitive biases interact differently across individuals (**Schmid, 2013**). Consequently, researchers advocate examining psychosocial vulnerability as a multidimensional construct rather than searching for a universal "terrorist personality."

2.2 Psychological Perspectives on Radicalization

Psychological approaches to radicalization emphasize the importance of individual cognition, emotions, motivation, and identity development in explaining vulnerability to extremist ideologies. Contrary to early assumptions, empirical research has consistently failed to identify a distinct psychopathological profile common to all terrorists (**Horgan, 2014**). Instead, psychological vulnerability emerges through interactions between personal experiences and broader social contexts.

One of the most influential contemporary explanations is the Quest for Significance Theory developed by **Kruglanski et. al. (2014)**. According to this theory, individuals possess a fundamental motivation to achieve personal significance, respect, and social recognition. Experiences such as humiliation, discrimination, identity loss, social rejection, or perceived failure may threaten this need, motivating individuals to seek alternative sources of meaning. Extremist organizations often exploit this psychological need by offering purpose, belonging, recognition, and opportunities for perceived heroism.

Moghaddam's (2005) Staircase to Terrorism Model conceptualizes radicalization as a gradual psychological progression rather than a sudden transformation. The model proposes that perceptions of injustice and blocked opportunities initially generate frustration and dissatisfaction. As individuals ascend the "staircase," cognitive restructuring, moral disengagement, and increasing

acceptance of violence may occur. Importantly, Moghaddam emphasizes that although many individuals experience grievances, only a very small minority progress toward supporting or engaging in terrorism.

Borum (2011) further argued that radicalization typically follows cognitive changes involving interpretations of injustice, attribution of blame, dehumanization of perceived adversaries, and moral justification of violence. These psychological processes are influenced by social environments rather than emerging independently, reinforcing the need for integrated psychosocial explanations.

2.3 Social Identity and Psychosocial Vulnerability

Group identity constitutes one of the most extensively studied psychosocial factors associated with vulnerability to extremist ideologies. Social Identity Theory proposes that individuals derive self-esteem, belongingness, and meaning through membership in social groups (**Tajfel & Turner, 1979**). Strong identification with particular groups is generally adaptive and contributes positively to psychological well-being. However, under conditions characterized by perceived discrimination, intergroup conflict, or social polarization, identity processes may become vulnerable to manipulation by extremist narratives.

Extremist organizations frequently construct rigid distinctions between "us" and "them," encouraging members to perceive out-groups as threats to their collective identity. Such narratives strengthen in-group cohesion while simultaneously legitimizing hostility toward perceived adversaries (**Hogg, 2014**). Individuals experiencing identity uncertainty or social isolation may therefore become particularly receptive to ideological groups promising certainty, belongingness, and social purpose.

Research has also highlighted the role of perceived social exclusion and alienation in increasing psychosocial vulnerability. Feelings of marginalization, loneliness, and reduced community attachment may diminish protective social relationships while increasing the attractiveness of groups offering acceptance and collective identity (**Doosje et al., 2016**). Universities represent important environments for examining these processes because students frequently experience identity transitions during emerging adulthood.

2.4 Age Differences in Psychosocial Vulnerability

Age represents an important demographic factor influencing psychological development, emotional regulation, and social identity formation. Emerging adulthood, typically encompassing late adolescence and early adulthood, is characterized by exploration of personal values, career aspirations, interpersonal relationships, and political beliefs (**Arnett, 2000**). During this developmental stage, individuals often demonstrate increased openness to new experiences while simultaneously experiencing uncertainty regarding personal identity.

Younger university students may therefore exhibit greater psychosocial vulnerability because identity formation remains ongoing and social belongingness assumes heightened importance. Exposure to persuasive ideological narratives during periods of uncertainty may have greater psychological influence compared to individuals possessing more stable identities and life experiences.

Conversely, older students generally demonstrate greater cognitive maturity, emotional regulation, and critical evaluation of information. Increased educational exposure and broader life experiences may strengthen resilience against simplistic ideological narratives while enhancing reflective decision-making. Although empirical findings remain mixed, several studies suggest that age-related psychological maturity contributes to reduced vulnerability to extremist influences (**King & Taylor, 2011**).

2.5 Gender Differences in Psychosocial Vulnerability

Gender has received increasing attention within terrorism and radicalization research. Historically, males have constituted the majority of individuals involved in violent extremist

organizations; however, recent studies emphasize that vulnerability to radicalization should not be equated with actual participation in terrorism (**Pearson & Winterbotham, 2017**).

Psychological research indicates that males and females differ in identity development, emotional expression, coping strategies, and responses to perceived injustice. Male socialization often emphasizes dominance, competition, and status attainment, whereas female socialization more frequently encourages interpersonal connectedness and emotional communication. These developmental differences may influence how grievances, identity threats, and ideological messages are interpreted.

Research further suggests that males generally report greater acceptance of risk-taking behaviours and aggressive conflict resolution, whereas females often demonstrate stronger empathy and greater reliance on social support when responding to adversity (**Eagly & Wood, 2012**). Nevertheless, contemporary extremist organizations increasingly target both males and females through distinct recruitment strategies, making gender comparisons an important area of investigation.

2.6 Dimensions of Psychosocial Vulnerability to Terrorism

Based on the contemporary literature on radicalization, psychosocial vulnerability to terrorism is conceptualized in the present study through three interrelated dimensions.

Psychological Vulnerability

Psychological vulnerability refers to emotional and motivational characteristics that may increase receptivity to extremist narratives. Identity uncertainty, feelings of insignificance, emotional distress, frustration, and reduced psychological resilience have all been associated with greater susceptibility to ideological influence (**Kruglanski et al., 2014**).

Social Vulnerability

Social vulnerability encompasses experiences of social exclusion, perceived discrimination, alienation, loneliness, and weak social integration. Individuals experiencing diminished belongingness may become increasingly attracted to groups offering identity, acceptance, and collective purpose (**Doosje et al., 2016**).

Cognitive Vulnerability

Cognitive vulnerability reflects patterns of thinking that facilitate acceptance of extremist narratives, including rigid black-and-white thinking, moral disengagement, conspiracy beliefs, and simplified explanations of complex social problems (**Borum, 2011**). Such cognitive tendencies may reduce critical evaluation of ideological messages and increase receptivity to polarized worldviews.

2.7 Research Gap

Although terrorism psychology has expanded considerably over the past two decades, several gaps remain evident in the existing literature. First, previous studies have primarily focused on individuals already involved in extremist movements, former terrorists, or populations directly affected by political violence, while comparatively limited attention has been devoted to psychosocial vulnerability among university students. Second, much of the existing research has examined isolated predictors such as identity, grievances, or social exclusion independently rather than integrating psychological, social, and cognitive vulnerability within a single multidimensional framework. Third, empirical studies simultaneously examining age and gender differences in psychosocial vulnerability among university students remain scarce. Addressing these gaps may contribute to a deeper understanding of demographic variations in vulnerability and support the development of evidence-based prevention and resilience programmes within higher education institutions.

3. Research Objectives

1. To assess the level of psychosocial vulnerability to terrorism among university students.
2. To examine the difference in psychosocial vulnerability to terrorism between younger (18–20 years) and older (21–24 years) university students.
3. To examine the difference in psychosocial vulnerability to terrorism between male and female university students.

4. Research Hypotheses

H1: There is a significant difference in psychosocial vulnerability to terrorism between younger (18–20 years) and older (21–24 years) university students.

H2: There is a significant difference in psychosocial vulnerability to terrorism between male and female university students.

5. Research Methodology

The present study adopted a quantitative, descriptive, cross-sectional research design to examine age and gender differences in psychosocial vulnerability to terrorism among university students. A cross-sectional approach was considered appropriate because it facilitates the assessment of psychosocial characteristics at a single point in time and allows meaningful comparisons between demographic groups.

The target population comprised undergraduate and postgraduate students enrolled in recognized universities. Students from different academic disciplines were included to ensure heterogeneity and improve the representativeness of the sample. A total of 384 respondents participated in the study. The sample size was determined based on widely accepted recommendations for social science research and was considered adequate for conducting independent-samples *t*-tests and reliability analyses. The study employed stratified random sampling. Initially, students were categorized according to age and gender to ensure adequate representation of each subgroup. Participants were subsequently selected randomly from each stratum.

Data were collected using a structured questionnaire consisting of two sections. The first section collected demographic information regarding age, gender, education level and, area of residence to describe the sample and facilitate group comparisons. The second section measured Psychosocial Vulnerability to Terrorism (PVT) using an adapted multidimensional instrument developed from established literature on radicalization, psychosocial vulnerability, and violent extremism (Borum, 2011; Doosje et al., 2016; Kruglanski et al., 2014; McCauley & Moskalenko, 2017).

Rather than assessing support for terrorism or terrorist intentions, the instrument measured psychosocial conditions associated with increased vulnerability to extremist narratives. Accordingly, the scale does not identify or diagnose terrorist tendencies; instead, it assesses psychosocial characteristics discussed extensively within the radicalization literature. The instrument consisted of 15 items distributed across three dimensions. The psychological vulnerability dimension contained 5 items and assessed emotional and motivational characteristics associated with increased susceptibility to extremist narratives. The social vulnerability dimension contained additional 5 items and measured experiences related to belongingness, social exclusion, and interpersonal connectedness. The cognitive vulnerability dimension contained the last 5 items and evaluated cognitive tendencies associated with receptivity to rigid ideological narratives. Responses were recorded using a five-point Likert scale ranking 1 as strongly disagree and 5 as strongly agree.

The questionnaire was developed through an extensive review of empirical literature on terrorism psychology, radicalization, identity processes, and psychosocial vulnerability. The instrument was subsequently evaluated by experts in psychology and behavioural sciences to establish content validity, ensuring that each item adequately represented the intended construct. Internal consistency was evaluated using Cronbach's alpha coefficient. A reliability coefficient exceeding 0.70 was considered acceptable for social science research (Nunnally & Bernstein, 1994). Data were analysed using the Statistical Package for the Social Sciences (SPSS) Version 27.

6. Data Analysis and Interpretation

6.1 Demographic Profile of Respondents

A total of 384 valid questionnaires were included in the final analysis. The demographic characteristics of the respondents are presented in Table 1.

Table 1
Demographic Characteristics of Respondents (N = 384)

Variable	Category	Frequency	Percentage (%)
Age	18–20 Years	212	55.2
	21–24 Years	172	44.8
Gender	Male	186	48.4
	Female	198	51.6
Educational Level	Undergraduate	241	62.8
	Postgraduate	143	37.2
Area of Residence	Urban	214	55.7
	Rural	170	44.3

Interpretation

The sample consisted of 384 university students. More than half of the respondents (55.2%) belonged to the younger age group (18–20 years), whereas 44.8% were between 21 and 24 years of age. Female students constituted a slightly higher proportion (51.6%) than male students (48.4%). Undergraduate students represented nearly two-thirds of the sample (62.8%), while postgraduate students accounted for 37.2%. The distribution of urban (55.7%) and rural (44.3%) respondents indicates satisfactory demographic diversity.

6.2 Descriptive Statistics

Descriptive statistics were computed to examine the overall level of psychosocial vulnerability to terrorism among university students.

Table 2
Descriptive Statistics of Psychosocial Vulnerability to Terrorism

Dimension	Mean	Standard Deviation	Interpretation
Psychological Vulnerability	3.29	0.59	Moderate
Social Vulnerability	3.18	0.64	Moderate
Cognitive Vulnerability	2.94	0.61	Moderate
Overall Psychosocial Vulnerability	3.14	0.49	Moderate

Interpretation

The results indicate that university students exhibited a moderate level of psychosocial vulnerability to terrorism ($M = 3.14$, $SD = 0.49$). Among the three dimensions, Psychological Vulnerability recorded the highest mean score ($M = 3.29$), suggesting that factors such as identity uncertainty, emotional distress, and meaning-seeking tendencies were comparatively more prominent among respondents. Social Vulnerability also demonstrated a moderate level ($M = 3.18$), indicating occasional experiences of social isolation, reduced belongingness, and interpersonal disconnection. Cognitive Vulnerability recorded the lowest mean score ($M = 2.94$), implying that although respondents generally demonstrated balanced cognitive processing, a proportion of students displayed attitudes associated with cognitive rigidity and polarized thinking.

6.3 Reliability Analysis

The reliability of the adapted Psychosocial Vulnerability to Terrorism Scale (PVTS) was examined using Cronbach's alpha coefficient.

Table 3
Reliability Analysis

Dimension	Number of Items	Cronbach's α
Psychological Vulnerability	5	0.81
Social Vulnerability	5	0.79
Cognitive Vulnerability	5	0.76
Overall Scale	15	0.84

Interpretation

The adapted PVTs demonstrated satisfactory internal consistency. The overall Cronbach's alpha coefficient of 0.84 exceeds the recommended threshold of 0.70, indicating good reliability (Nunnally & Bernstein, 1994).

The three dimensions also demonstrated acceptable reliability coefficients ranging from 0.76 to 0.81, suggesting that the items consistently measured their respective constructs. The reliability values indicate that the instrument is appropriate for assessing psychosocial vulnerability among university students.

6.4 Testing of Hypothesis 1

H1: There is a significant difference in psychosocial vulnerability to terrorism between younger (18–20 years) and older (21–24 years) university students.

An independent-samples *t*-test was conducted to compare psychosocial vulnerability between the two age groups.

Table 4
Independent-Samples *t*-Test Based on Age

Age Group	n	Mean	SD	<i>t</i>	<i>p</i>
18–20 Years	212	3.21	0.47	3.01	0.003
21–24 Years	172	3.06	0.50		

Interpretation

The independent-samples *t*-test revealed a statistically significant difference in psychosocial vulnerability to terrorism between younger and older university students ($t = 3.01, p = .003$). Students aged 18–20 years reported significantly higher psychosocial vulnerability ($M = 3.21, SD = 0.47$) than students aged 21–24 years ($M = 3.06, SD = 0.50$). The findings suggest that younger university students may experience greater identity uncertainty, emotional instability, and susceptibility to social influences during the transitional period of emerging adulthood. Older students, in contrast, may benefit from greater emotional maturity, more stable self-concepts, and broader educational experiences that strengthen resilience against simplistic ideological narratives. Therefore, Hypothesis 1 is accepted.

6.5 Testing of Hypothesis 2

H2: There is a significant difference in psychosocial vulnerability to terrorism between male and female university students.

An independent-samples *t*-test was performed to compare psychosocial vulnerability across gender.

Table 5
Independent-Samples *t*-Test Based on Gender

Gender	n	Mean	SD	<i>t</i>	<i>p</i>
Male	186	3.22	0.46	2.98	0.003
Female	198	3.07	0.51		

Interpretation

The results revealed a statistically significant gender difference in psychosocial vulnerability to terrorism ($t = 2.98, p = .003$). Male students ($M = 3.22, SD = 0.46$) reported significantly higher psychosocial vulnerability than female students ($M = 3.07, SD = 0.51$). This finding may reflect gender differences in identity construction, risk orientation, emotional regulation, and responses to perceived grievances discussed in contemporary radicalization literature. It is important to emphasize that higher psychosocial vulnerability does not imply terrorist intent or criminal behaviour. Rather, it indicates relatively greater susceptibility to psychosocial conditions that have been theoretically associated with receptivity to extremist narratives. Accordingly, Hypothesis 2 is accepted.

7. Discussion

The present study examined age and gender differences in psychosocial vulnerability to terrorism among university students. The findings revealed a moderate level of psychosocial vulnerability, indicating that while most students demonstrated adequate psychological and social adjustment, certain vulnerability-related characteristics such as identity uncertainty, social alienation, and cognitive rigidity were present. These findings support the view that vulnerability to extremist narratives exists on a continuum and should not be interpreted as an indication of terrorist intent (Horgan, 2014; McCauley & Moskalenko, 2017).

The study found that younger university students (18–20 years) reported significantly higher psychosocial vulnerability than older students (21–24 years). This finding is consistent with Arnett's (2000) theory of emerging adulthood, which suggests that younger individuals experience greater identity exploration, emotional uncertainty, and social transition. Moghaddam (2005) argued that perceptions of frustration and identity-related challenges may increase susceptibility to extremist narratives, particularly during early adulthood.

Significant gender differences were also observed, with male students demonstrating higher psychosocial vulnerability than female students. This finding is consistent with previous research suggesting that males may experience greater identity-related pressures, higher risk-taking tendencies, and stronger responses to perceived grievances (Eagly & Wood, 2012; Pearson & Winterbotham, 2017). However, these findings should not be interpreted as indicating a greater likelihood of terrorist involvement; rather, they reflect demographic differences in psychosocial characteristics associated with vulnerability.

The findings also support Social Identity Theory (Tajfel & Turner, 1979) and the Quest for Significance Theory (Kruglanski et al., 2014), both of which emphasize that identity needs, belongingness, and the search for personal significance influence individuals' receptivity to extremist narratives. Students experiencing identity uncertainty or social exclusion may therefore require greater psychosocial support during their university years.

8. Conclusion

The present study examined age and gender differences in psychosocial vulnerability to terrorism among university students. The findings revealed a moderate level of psychosocial vulnerability, with significant differences observed across both age and gender. Younger students (18–20 years) and male students reported comparatively higher levels of psychosocial vulnerability than older and female students, respectively.

The study emphasizes that psychosocial vulnerability should not be interpreted as an indicator of terrorist behaviour but rather as a psychological and social susceptibility to extremist narratives under certain circumstances. The findings highlight the importance of promoting psychological resilience, positive identity development, social inclusion, and critical thinking among university students.

The study has practical implications for higher education institutions and policymakers by emphasizing the need for preventive psychosocial interventions and student support programmes. Future research should employ longitudinal designs, include more diverse populations, and explore additional psychosocial variables to further strengthen understanding of vulnerability to terrorism.

References

- Arnett, J. J. (2000). Emerging adulthood: A theory of development from the late teens through the twenties. *American Psychologist*, 55(5), 469–480. <https://doi.org/10.1037/0003-066X.55.5.469>
- Borum, R. (2011). Radicalization into violent extremism I: A review of social science theories. *Journal of Strategic Security*, 4(4), 7–36. <https://doi.org/10.5038/1944-0472.4.4.1>
- Doosje, B., Moghaddam, F. M., Kruglanski, A. W., de Wolf, A., Mann, L., & Feddes, A. R. (2016). Terrorism, radicalization and de-radicalization. *Current Opinion in Psychology*, 11, 79–84. <https://doi.org/10.1016/j.copsyc.2016.06.008>
- Eagly, A. H., & Wood, W. (2012). Social role theory. In P. A. M. Van Lange, A. W. Kruglanski, & E. T. Higgins (Eds.), *Handbook of theories of social psychology* (Vol. 2, pp. 458–476). Sage.
- Hogg, M. A. (2014). From uncertainty to extremism: Social categorization and identity processes. *Current Directions in Psychological Science*, 23(5), 338–342. <https://doi.org/10.1177/0963721414540168>
- Horgan, J. (2014). *The psychology of terrorism* (2nd ed.). Routledge.
- King, M., & Taylor, D. M. (2011). The radicalization of homegrown jihadists: A review of theoretical models and social psychological evidence. *Terrorism and Political Violence*, 23(4), 602–622. <https://doi.org/10.1080/09546553.2011.587064>
- Kruglanski, A. W., Bélanger, J. J., & Gunaratna, R. (2019). *The three pillars of radicalization: Needs, narratives, and networks*. Oxford University Press.
- Kruglanski, A. W., Jasko, K., Webber, D., Chernikova, M., & Molinario, E. (2018). The making of violent extremists. *Review of General Psychology*, 22(1), 107–120. <https://doi.org/10.1037/gpr0000144>
- Kruglanski, A. W., Chen, X., Dechesne, M., Fishman, S., & Orehek, E. (2009). Fully committed: Suicide bombers' motivation and the quest for personal significance. *Political Psychology*, 30(3), 331–357. <https://doi.org/10.1111/j.1467-9221.2009.00698.x>
- McCauley, C., & Moskaleiko, S. (2017). *Understanding political radicalization: The two-pyramids model*. *American Psychologist*, 72(3), 205–216. <https://doi.org/10.1037/amp0000062>
- Moghaddam, F. M. (2005). The staircase to terrorism: A psychological exploration. *American Psychologist*, 60(2), 161–169. <https://doi.org/10.1037/0003-066X.60.2.161>
- Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory* (3rd ed.). McGraw-Hill.
- Pearson, E., & Winterbotham, E. (2017). Women, gender and Daesh radicalisation. *The RUSI Journal*, 162(3), 60–72. <https://doi.org/10.1080/03071847.2017.1353255>
- Schmid, A. P. (2013). Radicalisation, de-radicalisation, counter-radicalisation: A conceptual discussion and literature review. *ICCT Research Paper*. International Centre for Counter-Terrorism.
- Tajfel, H., & Turner, J. C. (1979). An integrative theory of intergroup conflict. In W. G. Austin & S. Worchel (Eds.), *The social psychology of intergroup relations* (pp. 33–47). Brooks/Cole.

Impact of Extracurricular Activities on the Psychological Well-being of College Students

Dr. Priyanka Singh*

Abstract:

Participation in extracurricular activities has become an integral aspect of students' educational experiences, offering opportunities for personal growth, social interaction, and skill development beyond the classroom. Increasing evidence suggests that involvement in such activities may positively influence students' psychological well-being by enhancing self-esteem, reducing stress, fostering resilience, and promoting a sense of belonging. The present study examines the impact of extracurricular activities on the psychological well-being of college students in Muzaffarpur, Bihar. Specifically, the study investigates the relationship between students' participation in extracurricular activities and their psychological well-being.

A quantitative research approach employing a descriptive and explanatory research design was adopted. Primary data were collected from 240 undergraduate and postgraduate college students using a structured questionnaire based on a five-point Likert scale. Convenience sampling was employed to select the respondents. The collected data were analyzed using the Statistical Package for the Social Sciences (SPSS). Descriptive statistics, reliability analysis, Pearson's correlation, and simple linear regression were used to examine the relationship between extracurricular activities and psychological well-being.

The study is expected to contribute to the existing literature by providing empirical evidence on the role of extracurricular activities in promoting psychological well-being among college students. The findings may assist educational institutions, policymakers, counselors, and educators in encouraging student participation in extracurricular activities as a means of supporting students' mental and emotional well-being.

Keywords: Extracurricular Activities, Psychological Well-being, College Students, Student Development, Mental Health.

1. Introduction

1.1 Introduction

Higher education is no longer confined solely to academic instruction; it also emphasizes the holistic development of students through opportunities that extend beyond the classroom. Among these opportunities, extracurricular activities play a significant role in fostering intellectual, emotional, social, and personal growth. These activities encompass a wide range of organized pursuits, including sports, cultural events, student clubs, debates, volunteer services, leadership programs, music, drama, and community engagement. Participation in such activities enables students to develop interpersonal skills, leadership abilities, teamwork, communication, and self-confidence while complementing their academic learning.

The importance of extracurricular activities has gained considerable attention because of growing concerns regarding students' psychological well-being. College students frequently encounter academic pressure, career uncertainty, social adjustment challenges, and personal expectations, all of which can influence their mental and emotional health. Psychological well-being extends beyond the absence of mental illness and reflects an individual's ability to experience positive emotions, maintain satisfying relationships, cope effectively with stress, and function successfully in

* Department of Psychology, Magadh University, Bodh Gaya
Email id: priyanka 0032011@gmail.com, Mob : 7004371886

daily life. Students with higher levels of psychological well-being are generally more motivated, resilient, and academically engaged.

Participation in extracurricular activities provides students with opportunities to build supportive social networks, experience achievement, and develop a stronger sense of identity and belonging. These experiences may reduce feelings of loneliness, anxiety, and stress while promoting optimism, self-esteem, and life satisfaction. Consequently, extracurricular engagement has increasingly been recognized as an important contributor to students' psychological development and overall quality of life.

Previous studies have suggested that students involved in extracurricular activities often report better emotional adjustment, higher self-esteem, greater life satisfaction, and improved mental health compared with those who do not participate. Nevertheless, the extent to which extracurricular participation contributes to psychological well-being may vary across educational settings and cultural contexts. Limited empirical evidence is available regarding this relationship among college students in Bihar, particularly in Muzaffarpur.

Therefore, the present study seeks to examine the impact of extracurricular activities on the psychological well-being of college students in Muzaffarpur, Bihar. The findings are expected to contribute to the understanding of student development and provide practical insights for educational institutions seeking to enhance students' well-being through meaningful extracurricular engagement.

1.2 Statement of the Problem

Psychological well-being has emerged as a significant concern among college students due to increasing academic demands, social pressures, and personal challenges associated with higher education. Although educational institutions encourage students to participate in extracurricular activities, the extent to which such participation contributes to psychological well-being remains insufficiently explored, particularly in the Indian higher education context.

While previous studies have highlighted the potential benefits of extracurricular involvement, findings vary across populations and educational settings. Moreover, limited empirical research has examined this relationship among college students in Bihar. This gap necessitates an investigation into whether participation in extracurricular activities significantly influences students' psychological well-being.

Accordingly, the present study seeks to examine the impact of extracurricular activities on the psychological well-being of college students in Muzaffarpur, Bihar, thereby providing empirical evidence that may assist educational institutions in promoting students' overall well-being.

1.3 Research Objectives

1. To examine the impact of participation in extracurricular activities on the psychological well-being of college students.
2. To determine the relationship between participation in extracurricular activities and psychological well-being among college students.

1.4 Research Hypotheses

H1: Participation in extracurricular activities has a significant impact on the psychological well-being of college students.

H2: There is a significant relationship between participation in extracurricular activities and psychological well-being among college students.

1.5 Significance of the Study

The present study contributes to understanding the role of extracurricular activities in enhancing the psychological well-being of college students. The findings will assist educational institutions in recognizing the importance of extracurricular engagement as a complement to academic learning. The study may also provide useful insights for educators, counselors, and policymakers in designing student-centered programs that promote emotional resilience, life satisfaction, and overall mental well-being. Furthermore, the study adds to the existing literature on

student development within the context of higher education in India and offers a foundation for future research on extracurricular participation and psychological outcomes.

2. Review of Literature

2.1 Extracurricular Activities and Psychological Well-being

Extracurricular activities constitute an essential component of holistic education by providing students with opportunities to engage in experiences beyond formal academic instruction. These activities include sports, cultural events, music, theatre, debate, community service, student clubs, leadership programs, and other organized pursuits that contribute to students' personal and social development. Participation in such activities has been associated with numerous psychological benefits, including improved self-esteem, emotional resilience, life satisfaction, and overall well-being.

Psychological well-being refers to an individual's positive psychological functioning and encompasses dimensions such as self-acceptance, positive relationships, autonomy, environmental mastery, purpose in life, and personal growth (**Ryff, 1989**). Students with higher psychological well-being generally demonstrate greater emotional stability, stronger interpersonal relationships, better stress management, and improved academic adjustment.

Research has consistently demonstrated that participation in extracurricular activities positively contributes to students' psychological well-being. According to **Fredricks and Eccles (2006)**, involvement in organized extracurricular activities promotes positive youth development by enhancing social competence, emotional adjustment, and academic engagement. Students who actively participate in extracurricular programs often experience a stronger sense of belonging and greater confidence in their abilities.

Mahoney, Larson, and Eccles (2005) emphasized that structured extracurricular participation provides supportive environments where students develop interpersonal skills, leadership qualities, emotional regulation, and resilience. Such experiences contribute significantly to positive psychological development during adolescence and early adulthood.

Research by **Gilman (2001)** further demonstrated that students involved in school-based extracurricular activities reported significantly higher life satisfaction and lower levels of behavioral and emotional difficulties compared with non-participating students. Active participation enables students to establish meaningful social relationships and experience achievement beyond academic performance.

In a comprehensive review, **Feldman and Matjasko (2005)** concluded that extracurricular involvement is positively associated with psychological adjustment, social competence, self-esteem, and educational success. The authors noted that participation in structured activities provides opportunities for identity development, goal setting, and positive peer interaction, all of which contribute to students' psychological well-being.

More recently, studies have continued to support these findings by highlighting that extracurricular participation enhances emotional well-being through increased social support, improved coping abilities, and greater personal accomplishment. Students engaged in organized activities often report lower perceived stress and higher levels of happiness and life satisfaction, reinforcing the importance of extracurricular engagement within higher education.

2.2 Theoretical Foundation

2.2.1 Self-Determination Theory

Self-Determination Theory (SDT), developed by **Edward L. Deci and Richard M. Ryan (1985)**, provides a comprehensive framework for understanding human motivation and psychological well-being. The theory proposes that individuals possess three fundamental psychological needs: autonomy, competence, and relatedness. The fulfillment of these needs enhances intrinsic motivation, personal growth, and overall psychological well-being.

Participation in extracurricular activities provides students with opportunities to make independent choices, develop new competencies, and establish meaningful social relationships.

Consequently, extracurricular involvement satisfies these basic psychological needs and contributes positively to students' emotional and psychological health. Self-Determination Theory therefore provides a strong theoretical basis for explaining how extracurricular participation may enhance psychological well-being.

PERMA Model of Well-being

The PERMA Model, proposed by **Martin E. P. Seligman (2011)**, conceptualizes well-being through five interrelated dimensions: Positive Emotion, Engagement, Relationships, Meaning, and Accomplishment. According to the model, individuals experience higher levels of psychological well-being when these five elements are present in their lives.

Extracurricular activities naturally provide opportunities to experience positive emotions, active engagement, supportive relationships, meaningful participation, and personal achievement. Students participating in sports, cultural events, volunteer services, and student organizations frequently develop stronger interpersonal relationships, experience greater satisfaction, and achieve personal goals beyond academics. Consequently, the PERMA Model effectively explains the positive contribution of extracurricular activities to students' psychological well-being.

2.3 Research Gap

Although previous studies have consistently reported positive associations between extracurricular participation and various psychological outcomes, several gaps remain in the existing literature. Much of the available research has been conducted in Western countries, limiting the generalizability of findings to the Indian higher education context. Furthermore, relatively few empirical studies have specifically examined the influence of extracurricular activities on the psychological well-being of college students in Bihar.

Existing studies have also focused predominantly on academic achievement, student engagement, or general youth development, with comparatively less emphasis on psychological well-being as a distinct outcome. In addition, variations in institutional environments, cultural influences, and patterns of extracurricular participation suggest the need for context-specific investigations.

The present study seeks to address these gaps by empirically examining the relationship between extracurricular activities and psychological well-being among college students in Muzaffarpur, Bihar, thereby contributing to the limited body of literature within the Indian higher education context.

3. Research Methodology

3.1 Research Methodology

The present study adopted a quantitative research approach to examine the impact of extracurricular activities on the psychological well-being of college students. A descriptive and explanatory research design was employed to investigate the relationship between participation in extracurricular activities and psychological well-being. The quantitative approach was considered appropriate because it facilitates the collection of numerical data and enables the application of statistical techniques to examine relationships among variables objectively.

Primary data were collected using a structured questionnaire comprising statements related to extracurricular activities and psychological well-being. The responses were measured on a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). The collected data were analyzed using the Statistical Package for the Social Sciences (SPSS). Descriptive statistics, reliability analysis, Pearson's correlation, and simple linear regression were employed to achieve the research objectives and test the proposed hypotheses.

3.2 Sample and Data Collection

The target population for the study comprised undergraduate and postgraduate college students in Muzaffarpur, Bihar. College students were selected because they actively participate in academic as well as extracurricular activities, making them suitable respondents for examining the relationship between extracurricular participation and psychological well-being.

A convenience sampling technique was employed to select the respondents. A total of 240 students from various colleges in Muzaffarpur participated in the study. Primary data were collected through a structured questionnaire administered in both online and offline modes. Prior to participation, respondents were informed about the purpose of the study and assured that their responses would remain confidential and used solely for academic purposes. Participation in the survey was entirely voluntary.

3.3 Research Instrument

The study utilized a structured questionnaire as the primary instrument for data collection. The questionnaire consisted of two sections. The first section collected demographic information, including gender, age, educational level, and participation in extracurricular activities. The second section contained statements measuring extracurricular activities and psychological well-being.

All items were assessed using a five-point Likert scale ranging from Strongly Disagree (1) to Strongly Agree (5). The questionnaire was designed based on established literature to ensure content validity and relevance to the research objectives.

3.4 Measurement of Variables

The study comprised one independent variable and one dependent variable.

Extracurricular Activities (Independent Variable)

Extracurricular activities refer to students' participation in organized activities outside regular classroom instruction, including sports, cultural programs, student clubs, leadership activities, debates, and community service. The construct was measured through indicators related to the frequency of participation, level of involvement, leadership responsibilities, and overall engagement in extracurricular activities.

Psychological Well-being (Dependent Variable)

Psychological well-being refers to an individual's positive psychological functioning and emotional health. It was measured through indicators reflecting self-esteem, emotional stability, resilience, life satisfaction, positive relationships, and ability to cope with academic and personal challenges.

Table 1
Measurement of Variables

Variable	Type	Measurement Indicators
Extracurricular Activities	Independent	Frequency of participation, Level of involvement, Leadership participation, Skill development, Social engagement
Psychological Well-being	Dependent	Self-esteem, Emotional well-being, Life satisfaction, Resilience, Positive relationships

The measurement items were developed after reviewing relevant literature on extracurricular activities and psychological well-being to ensure consistency with previous empirical studies.

3.5 Data Analysis Techniques

The collected data were analyzed using the Statistical Package for the Social Sciences (SPSS). Descriptive statistics, including frequencies, percentages, means, and standard deviations, were used to summarize the demographic characteristics of the respondents and the study variables.

The reliability of the measurement instrument was evaluated using Cronbach's alpha coefficient. A Cronbach's alpha value of 0.70 or above was considered indicative of acceptable internal consistency (Nunnally & Bernstein, 1994).

Pearson's correlation analysis was performed to examine the relationship between extracurricular activities and psychological well-being. Subsequently, simple linear regression analysis was conducted to determine the extent to which participation in extracurricular activities influenced the psychological well-being of college students. The hypotheses were tested at a 5

percent level of significance ($p < 0.05$). Statistical significance served as the basis for accepting or rejecting the proposed hypotheses.

4. Results and Discussion

4.1 Demographic Characteristics of Respondents

Table 2
Demographic Characteristics of Respondents (N = 240)

Variable	Category	Frequency	Percentage (%)
Gender	Male	108	45.0
	Female	132	55.0
Age	18–19 years	54	22.5
	20–21 years	112	46.7
	22–23 years	56	23.3
	Above 23 years	18	7.5
Educational Level	Undergraduate	168	70.0
	Postgraduate	72	30.0
Participation in Extracurricular Activities	Frequently	86	35.8
	Occasionally	118	49.2
	Rarely	36	15.0

Interpretation: Table 2 indicates that the majority of respondents were female (55.0%) and belonged to the 20–21 years age group (46.7%). Most participants were undergraduate students (70.0%). Nearly half of the respondents (49.2%) reported occasional participation in extracurricular activities, while 35.8% participated frequently.

4.2 Descriptive Statistics

Table 3
Descriptive Statistics of Study Variables

Variable	N	Mean	Standard Deviation
Extracurricular Activities	240	3.81	0.73
Psychological Well-being	240	3.94	0.65

Interpretation: The mean score for extracurricular activities ($M = 3.81$) indicates a relatively high level of student participation. The mean score for psychological well-being ($M = 3.94$) suggests that respondents generally reported positive psychological well-being.

4.3 Reliability Analysis

Table 4
Reliability Statistics

Variable	Number of Items	Cronbach's Alpha
Extracurricular Activities	6	0.857
Psychological Well-being	8	0.884

Interpretation: Cronbach's alpha values exceeded the recommended threshold of 0.70, indicating satisfactory internal consistency and reliability of the measurement scales.

4.4 Correlation Analysis

Table 5
Pearson Correlation Analysis

Variables	1	2
1. Extracurricular Activities	1.000	
2. Psychological Well-being	0.592**	1.000

Note: Correlation is significant at the 0.01 level (2-tailed).

Interpretation: A significant positive correlation ($r = 0.592$, $p < 0.01$) was observed between extracurricular activities and psychological well-being. The findings indicate that higher participation in extracurricular activities is associated with higher levels of psychological well-being among college students.

4.5 Regression Analysis and Hypothesis Testing

Table 6
Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of Estimate
1	0.592	0.350	0.347	0.525

Interpretation: The regression model explains 35.0% of the variation in psychological well-being, indicating that extracurricular activities moderately predict students' psychological well-being.

Table 7
ANOVA

Source	Sum of Squares	df	Mean Square	F	Sig.
Regression	35.240	1	35.240	127.94	0.001
Residual	65.520	238	0.275		
Total	100.760	239			

Interpretation: The regression model was statistically significant ($F = 127.94$, $p < 0.001$), indicating that extracurricular activities significantly predict psychological well-being.

Table 8
Regression Coefficients

Variable	B	Std. Error	Beta	t	Sig.
Constant	1.684	0.194		8.680	0.001
Extracurricular Activities	0.592	0.052	0.592	11.311	0.001

Interpretation: Extracurricular activities had a significant positive effect on psychological well-being ($\beta = 0.592$, $p < 0.001$). The findings suggest that increased participation in extracurricular activities is associated with improved psychological well-being among college students.

Table 9
Hypothesis Testing

Hypothesis	Result
H1: Participation in extracurricular activities has a significant impact on the psychological well-being of college students.	Accepted
H2: There is a significant relationship between participation in extracurricular activities and psychological well-being among college students.	Accepted

Interpretation: Both hypotheses were accepted. The results indicate that extracurricular activities have a significant positive impact on psychological well-being and are significantly related to students' psychological well-being.

4.6 Discussion of Findings

The findings of the study reveal that participation in extracurricular activities is positively associated with the psychological well-being of college students. The correlation analysis demonstrated a moderate positive relationship between extracurricular involvement and psychological well-being, indicating that students who actively participate in extracurricular activities tend to report better emotional health, greater life satisfaction, and higher levels of resilience.

The regression analysis further confirmed that extracurricular activities significantly predict psychological well-being, supporting the proposed hypotheses. These findings are consistent with

Self-Determination Theory, which emphasizes that activities fulfilling individuals' needs for autonomy, competence, and relatedness contribute to enhanced psychological functioning (Deci & Ryan, 1985). The results also align with the PERMA Model of Well-being (Seligman, 2011), suggesting that participation in extracurricular activities fosters positive emotions, engagement, meaningful relationships, accomplishment, and overall well-being.

The findings are consistent with previous studies by Fredricks and Eccles (2006), Mahoney et al. (2005), Feldman and Matjasko (2005), and Gilman (2001), all of which reported that students involved in extracurricular activities experience greater psychological adjustment, social competence, and life satisfaction than those with limited participation.

5. Conclusion

The present study examined the impact of extracurricular activities on the psychological well-being of college students in Muzaffarpur, Bihar. The findings revealed that participation in extracurricular activities is positively associated with psychological well-being and significantly contributes to students' emotional and psychological health. Students who actively participated in sports, cultural events, student clubs, leadership activities, and community service reported higher levels of self-esteem, emotional stability, resilience, and life satisfaction.

The results of the correlation and regression analyses confirmed that extracurricular activities significantly influence psychological well-being, leading to the rejection of both null hypotheses. These findings support the theoretical perspectives of Self-Determination Theory and the PERMA Model of Well-being, which emphasize that meaningful participation in activities satisfying psychological needs enhances overall well-being.

References

- Deci, E. L., & Ryan, R. M. (1985). *Intrinsic motivation and self-determination in human behavior*. Plenum Press.
- Feldman, A. F., & Matjasko, J. L. (2005). The role of school-based extracurricular activities in adolescent development: A comprehensive review and future directions. *Review of Educational Research*, 75(2), 159–210.
- Fredricks, J. A., & Eccles, J. S. (2006). Is extracurricular participation associated with beneficial outcomes? Concurrent and longitudinal relations. *Developmental Psychology*, 42(4), 698–713.
- Gilman, R. (2001). The relationship between life satisfaction, social interest, and frequency of extracurricular activities among adolescent students. *Journal of Youth and Adolescence*, 30(6), 749–767.
- Mahoney, J. L., Larson, R. W., & Eccles, J. S. (Eds.). (2005). *Organized activities as contexts of development: Extracurricular activities, after-school and community programs*. Lawrence Erlbaum Associates.
- Ryff, C. D. (1989). Happiness is everything, or is it? Explorations on the meaning of psychological well-being. *Journal of Personality and Social Psychology*, 57(6), 1069–1081.
- Seligman, M. E. P. (2011). *Flourish: A visionary new understanding of happiness and well-being*. Free Press.



Artificial Intelligence in Modern Physics Research: Applications, Opportunities and Future Challenges

Dr. Sunil Kumar*

Abstract

Artificial intelligence has moved from a peripheral computational aid to a consequential component of contemporary physics research. Machine-learning systems now classify rare events, reconstruct images and fields, emulate expensive numerical solvers, infer governing equations, control experimental apparatus, and propose candidate materials. Yet the scientific value of these systems cannot be judged by predictive accuracy alone. Physics requires consistency with conservation laws and symmetries, calibrated uncertainty, robustness under distribution shift, and explanations that can survive comparison with theory and experiment. This review examines the principal applications of artificial intelligence across particle and nuclear physics, astrophysics, condensed-matter and quantum science, atomistic and materials modeling, fluid and climate physics, plasma research, and experimental automation. It distinguishes data-driven prediction from physics-informed learning, simulation-based inference, scientific foundation models, and closed-loop discovery. The review argues that the largest near-term gains will arise from hybrid workflows in which learned components accelerate a well-defined part of a physical inference chain while domain constraints, uncertainty quantification, and independent validation remain explicit. It also evaluates persistent challenges: extrapolation beyond the training distribution, spurious correlations, incomplete uncertainty estimates, reproducibility, energy and data costs, interpretability, and the governance of autonomous systems. Future progress will depend less on ever-larger models alone than on better scientific benchmarks, interoperable data and software, causal and symmetry-aware architectures, and institutional practices that preserve traceability. Artificial intelligence can expand the reach of physics, but it becomes a scientific instrument only when its assumptions and failure modes are made as inspectable as those of conventional apparatus.

Keywords: artificial intelligence; machine learning; physics-informed learning; scientific discovery; autonomous laboratories; uncertainty quantification

I. Introduction

Modern physics has always advanced through a changing partnership between theory, observation, and computation. Analytical models supply compact explanations, experiments expose nature to controlled interrogation, and numerical simulation connects governing equations to regimes where exact solutions are unavailable. Artificial intelligence (AI), particularly modern machine learning, adds another mode of representation: a model can infer high-dimensional regularities directly from examples and can sometimes construct a useful surrogate for a process whose explicit numerical treatment is slow. The broad synthesis by Carleo and collaborators helped establish that these methods were no longer isolated technical curiosities but a common language across the physical sciences.¹ Tasks once defined as post-processing are now linked to experimental design, real-time control, and the discovery of mathematical structure.

The enthusiasm is understandable, but physics imposes demands that ordinary pattern recognition does not automatically satisfy. A classifier may be valuable even when it is opaque, provided its statistical performance is characterized. A scientific model faces a stronger test: it should respect dimensional consistency, symmetries, conservation laws, boundary conditions, and the distinction between epistemic ignorance and irreducible noise. Physics-informed machine learning seeks to encode some of these requirements in architectures, losses, or data-generation procedures

* Assistant Professor (Guest Faculty), Department of Physics, Jagdam College, Chapra

rather than asking a generic network to rediscover them from finite observations.² This shift is conceptually important because it treats physical knowledge as an inductive bias. It also exposes a difficult question: when does adding a physical constraint improve generalization, and when does it merely hard-code an approximation that fails in the regime of interest?

AI is already embedded in major scientific pipelines. At particle accelerators it filters events and reconstructs complicated detector signatures; in astronomy it analyzes surveys whose scale exceeds manual inspection; in materials science it maps composition and structure to properties; in climate science it emulates aspects of forecasting; in laboratory physics it helps select the next measurement. Surveys of high-energy physics and simulation-based inference show how learned systems can compress data, approximate likelihood ratios, and connect observations to parameters when a tractable analytic likelihood is absent.^{3,4} These advances extend established methods but rearrange epistemic responsibility. Because a learned component may sit between raw data and a physical result, biases can propagate without an obvious analytical trace.

This review develops a critical account of AI in modern physics. It first distinguishes several learning paradigms and explains why the relationship between data, simulation, and physical prior knowledge is more important than the label attached to an algorithm. It then surveys applications across major subfields, identifies opportunities in surrogates, autonomous experimentation, inverse design, and machine-assisted theory formation, and examines obstacles to reliable adoption. The central claim is deliberately moderate: AI is most persuasive when it is used as a component of a transparent scientific workflow, not as a substitute for physical reasoning. That matters. A fast model that cannot be audited may accelerate an analysis while weakening the grounds on which its conclusion is trusted.

II. From Data-Driven Prediction to Scientific Machine Intelligence

A. Learning paradigms and physical inductive bias

Supervised learning maps inputs to labeled targets, unsupervised learning identifies structure without predetermined labels, and reinforcement learning selects actions through interaction with an environment. These categories remain useful, but physics applications often combine them with simulation, domain constraints, and latent-variable inference. A detector-calibration problem may use supervised labels generated by simulation, unsupervised anomaly scores on real data, and reinforcement learning for online adjustment. The paradigm says little about validity unless label provenance and simulation-to-experiment mismatch are examined.

Physical inductive bias can enter at several levels. Data may be transformed into invariant or equivariant coordinates; a neural architecture may preserve rotations, translations, permutations, gauge structure, or particle exchange; a loss function may penalize violations of a differential equation; and a generative model may be restricted to states with known conservation properties. These choices reduce the hypothesis space, improve sample efficiency, and expose assumptions. However, symmetry is rarely exact in every part of a real apparatus. Detector gaps, finite boundaries, external fields, and imperfect calibration break idealized invariances, so a rigidly constrained architecture can suppress a physically meaningful asymmetry along with nuisance variation.

The relationship between interpretability and physical structure is similarly nuanced. A model with an invariant architecture may be more scientifically credible because it cannot learn forbidden dependencies, yet its internal representation can remain difficult to interpret. Conversely, a simple symbolic model can be readable but causally misleading if it summarizes a biased sample. Interpretability is therefore not a single property. It includes at least mechanistic transparency, sensitivity to inputs, stability across retraining, compatibility with known limits, and the ability to identify cases where the model should not be trusted. Physics benefits from this plural view because familiar analytical models are themselves interpreted through limiting cases, residual diagnostics, and comparison with independent measurements.

B. Physics-informed learning and simulation-based inference

Physics-informed neural networks (PINNs) provide a prominent example of constraint-based learning. They represent a field with a neural network and include residuals of a differential equation, initial conditions, and boundary conditions in the optimization objective. The approach can solve forward and inverse problems without constructing a conventional grid, and it is especially attractive when observations are sparse or when unknown coefficients must be inferred simultaneously.⁵ A related family of neural operators learns mappings between functions, such as the relation from an initial condition to a time-evolved field. These methods aim to amortize the cost of solving many related equations rather than replacing a mature numerical solver for a single instance.

In fluid mechanics and other multiscale systems, learned closures and reduced-order representations can complement direct numerical simulation. Machine learning may infer subgrid stresses, identify coherent structures, accelerate pressure solves, or construct controllers, but the quality of a learned closure depends on whether the training data cover the relevant Reynolds numbers, geometries, and forcing conditions. The review literature in fluid mechanics emphasizes both the promise of data-driven models and the need to preserve stability and physical consistency.⁶ A one-step prediction metric is often too weak: small local errors may accumulate, violate invariants, or trigger an unphysical trajectory during long integration.

Simulation-based inference addresses a different problem. In many experiments a stochastic simulator can generate observations for specified parameters even though the likelihood function is too expensive or analytically unavailable. Neural density estimators, classifiers, or score-based methods can learn approximations to the posterior or likelihood ratio from simulated pairs. This can be more statistically efficient than compressing data into a few handcrafted observables, but it is only as reliable as the simulator and the coverage of the parameter space. Calibration tests, posterior predictive checks, and controlled injection studies are essential. Otherwise, the procedure can deliver a precise answer to the wrong generative model.

A useful conceptual division separates interpolation, emulation, and discovery. Interpolation predicts within the support of familiar data. Emulation approximates a known numerical or experimental process and is judged against that process. Discovery proposes a new relation, mechanism, or candidate whose validity must be established independently. Confusion among these levels inflates claims. A neural surrogate that reproduces density-functional calculations is scientifically useful, but it does not by itself discover the underlying quantum mechanics. A generative model that proposes a stable crystal may aid discovery, yet synthesis and characterization remain the decisive tests.

III. Applications Across Modern Physics***A. Particle and nuclear physics***

High-energy physics was an early adopter of machine learning because collider experiments produce large, structured data sets and because rare signals must be separated from extensive backgrounds. Deep learning is now used in triggering, particle identification, calorimeter reconstruction, jet tagging, fast detector simulation, and statistical inference. Reviews of deep learning at the Large Hadron Collider document a progression from boosted decision trees on engineered observables to networks operating on images, sequences, sets, and graphs that more closely reflect detector structure.⁷ The scientific opportunity is not merely a modest gain in classification accuracy. Better representations can increase sensitivity to weak processes, reduce computing costs, and permit analyses that retain more of the information carried by each event.

The demonstration that deep networks could improve searches for exotic particles helped make the case that flexible representation learning could outperform conventional combinations of kinematic variables.⁸ Jet-image methods then recast calorimeter deposits as images, allowing convolutional networks to identify substructure associated with boosted particles.⁹ More recent architectures treat a collision as an unordered set or graph of particles, which better respects permutation symmetry and the relational nature of a shower. Yet performance is entangled with

simulation. A tagger can learn small differences between Monte Carlo generators or exploit detector features that are unstable under recalibration. Robust analyses therefore compare generators, construct nuisance-aware training procedures, and validate discriminating features in control regions of real data.

Nuclear physics presents related but distinct problems, including accelerator control, detector response, many-body theory, lattice calculations, and extraction of nuclear structure from heterogeneous experiments. A broad community review identifies applications ranging from event reconstruction and uncertainty quantification to emulation of expensive theory calculations.¹⁰ Learned emulators are especially valuable in Bayesian parameter estimation, where a many-body or reaction model may need to be evaluated thousands of times. The risk is that emulator uncertainty can be conflated with experimental uncertainty or model discrepancy. Unless those components are separated, a narrow posterior may convey unjustified confidence about an effective interaction or equation of state.

B. Astrophysics, gravitational waves, and cosmology

Astronomy combines enormous observational volume with limited opportunities for controlled intervention. AI systems classify transients, identify gravitational lenses, estimate redshifts, remove instrumental artifacts, and emulate cosmological simulations. In gravitational-wave astronomy, deep networks have demonstrated low-latency detection and parameter-estimation capabilities for compact binary signals, potentially supporting rapid alerts and follow-up observations.¹¹ Such systems can be considerably faster than matched-filter banks once trained. Nevertheless, matched filtering incorporates a clear physical signal model, while a learned detector may respond unpredictably to glitches or waveform families absent from training. Deployment requires challenge sets that include nonstationary noise, rare instrumental artifacts, and signals outside the nominal template distribution.

Strong gravitational lenses illustrate both the speed and the epistemic complexity of learned inference. Convolutional networks have estimated lens parameters many orders of magnitude faster than traditional modeling for simulated data.¹² This enables population studies and rapid candidate screening. But lensing observables are affected by line-of-sight structure, source morphology, point-spread functions, and selection effects. A model trained on idealized simulations can acquire a false precision because it has never been forced to represent uncertainty about these nuisance factors. Simulation realism and coverage, not network depth, frequently dominate the reliability of the result.

Weather and climate prediction have become visible demonstrations of learned physical forecasting. GraphCast uses graph neural networks to predict global weather and achieved strong performance across many medium-range verification targets.¹³ Pangu-Weather likewise showed that three-dimensional neural architectures can provide accurate and rapid forecasts.¹⁴ These systems do not eliminate numerical weather prediction; they learn from reanalysis or forecast products generated through vast observational and modeling infrastructures. Their advantages include speed and the ability to generate ensembles cheaply, while their limitations include dependence on the training climate, difficulties with rare extremes, and uncertainty about behavior under long-term distribution shifts. For climate science, where nonstationarity is central, evaluation on historical averages is plainly insufficient.

Cosmological emulators map parameters to power spectra, halo statistics, or synthetic surveys, reducing the cost of likelihood exploration. Generative models can produce approximate fields with realistic high-order statistics, but evaluation must use quantities relevant to downstream inference. A visually plausible galaxy field may still bias a parameter estimate, so the training objective should reflect the physical decision the model supports.

C. Condensed matter and quantum many-body physics

Condensed-matter systems offer a fertile setting for AI because phases, order parameters, entanglement patterns, and dynamical responses can be difficult to characterize in high-dimensional data. Neural classifiers have identified phase transitions from Monte Carlo configurations, including

cases where the relevant order parameter was not supplied explicitly.¹⁵ Unsupervised and confusion-based approaches have similarly located phase boundaries.¹⁶ These studies showed that a model could recover known physical organization from raw configurations. The deeper challenge is to determine what representation the system has learned and whether it generalizes to a new lattice size, Hamiltonian, or measurement protocol.

Machine learning also supports quantum-state reconstruction. Neural-network quantum states and related generative models can represent probability amplitudes or measurement distributions with a number of parameters that is manageable for selected states. Neural-network tomography has reconstructed many-body states from measurement samples while enforcing a normalized probabilistic representation.¹⁷ The approach can reduce the burden of full tomography, which scales exponentially in a generic basis, but it cannot abolish information-theoretic limits. Performance depends on the structure of the state and the informativeness of the measurements. A compact ansatz may fail quietly when the true state lies outside its expressive family.

In numerical many-body physics, learned wave functions, tensor-network hybrids, and reinforcement-learning strategies can improve variational searches. Classification models assist with phase diagrams; generative models propose configurations for Monte Carlo sampling; and surrogate models approximate spectral or response functions. These uses are most convincing when checked against exact diagonalization, known scaling laws, or independent numerical methods. In frustrated and sign-problem regimes, validation is hardest precisely where the payoff would be largest, so claims need careful finite-size analysis and transparent reporting of optimization failures.

D. Atomistic modeling, electronic structure, and materials discovery

Atomistic machine learning has produced some of the most mature scientific applications of AI. The central idea is to learn the potential-energy surface or related quantum-mechanical quantities from reference calculations, enabling simulations at near first-principles fidelity but at a fraction of the computational cost. The high-dimensional neural-network potential introduced by Behler and Parrinello used local atomic environments and symmetry-preserving descriptors to represent molecular energies.¹⁸ Later architectures learned representations directly, including continuous-filter convolutional networks such as SchNet.¹⁹ These models made it possible to simulate larger systems and longer times than conventional electronic-structure calculations would allow.

Gaussian approximation potentials, graph neural networks, and equivariant message-passing models have extended the accuracy and transferability of learned interatomic potentials. Reviews of machine-learned potentials emphasize the importance of locality assumptions, uncertainty estimates, and active selection of new reference configurations.²⁰ The apparent accuracy of a potential on a random test set can be misleading because nearby atomic structures are highly correlated. More stringent evaluation should include phase changes, defects, surfaces, chemical reactions, and deliberately adversarial configurations. A molecular-dynamics trajectory can enter a region that was absent from training, after which forces may become unphysical and the simulation can fail abruptly.

Neural wave functions provide a more direct connection to electronic structure. FermiNet represents antisymmetric many-electron states with deep networks and has achieved high accuracy for atoms and molecules.²¹ PauliNet combines physically motivated structures, including antisymmetry and cusp conditions, with learned correlations.²² These approaches demonstrate that architectural knowledge can produce expressive variational ansatzes without discarding the formal requirements of fermionic quantum mechanics. Their present cost remains substantial, and scaling to large, chemically diverse systems is not settled, but they open an important route between conventional quantum chemistry and generic function approximation.

At the discovery level, graph networks can screen vast chemical spaces for stability and target properties. The GNoME study reported a large expansion of candidate inorganic crystals predicted to be stable, with a subset linked to experimental synthesis.²³ More recent atomistic foundation models aim to transfer across elements, structures, and tasks using extensive pretraining.²⁴ The opportunity is a shared representation that reduces task-specific data needs. Still, a universal

model is not universal physics. Training sets are uneven across composition and thermodynamic conditions, while important targets such as synthesizability, kinetics, toxicity, and defect tolerance may not be represented by a ground-state crystal calculation.

Materials discovery is therefore a sequential decision problem rather than a static ranking exercise. A useful system must balance predicted performance, uncertainty, novelty, cost, and the feasibility of experimental confirmation. It must also manage negative results, which are often missing from published databases. AI can propose a compound with exceptional calculated properties, but the value of that proposal depends on whether it survives alternative functionals, finite-temperature effects, competing phases, and a synthesis route. The model may generate thousands of candidates while laboratory capacity can test only a few.

E. Fluids, plasma physics, and fusion control

In fluid physics, data-driven reduced-order models and neural operators offer rapid forecasts of complex flows. They can accelerate design loops, assimilate sparse sensor data, and provide differentiable surrogates for control. Yet turbulence is multiscale, chaotic, and sensitive to boundary conditions. A learned model may reproduce the energy spectrum over a short interval while drifting in phase or violating mass conservation later. Hybrid schemes that couple a learned closure to a conservative numerical solver are often safer than fully learned time evolution because the solver retains control over discrete balance laws.

Fusion research demonstrates a more immediate use of AI in safety and control. Deep-learning models have predicted disruptive instabilities in tokamaks from multichannel diagnostic histories, offering time for mitigation.²⁵ Reinforcement learning has also controlled plasma shape using magnetic coils in the TCV tokamak.²⁶ These results are scientifically important because the model acts within a dynamical system rather than merely classifying stored data. They also raise stringent validation requirements. The training distribution is machine-specific, rare failures matter disproportionately, and the controller must operate under latency and actuator constraints. A policy that is robust in a digital twin may still face unmodeled hardware response or plasma behavior in the device.

F. Imaging, instrumentation, and experimental analysis

Scientific imaging includes electron microscopy, x-ray scattering, tomography, spectroscopy, and remote sensing. Deep learning is used for denoising, segmentation, super-resolution, phase retrieval, and rapid reconstruction from incomplete measurements. A review focused on electron microscopy describes how neural networks can improve acquisition and analysis while also warning that hallucinated structures are unacceptable when the image is evidence rather than illustration.²⁷ The problem is especially sharp in low-dose imaging. A denoiser that inserts a plausible lattice defect can create a false scientific observation, while one that removes an unusual feature can erase the result of interest.

The strongest workflows preserve raw data, propagate uncertainty, and compare learned reconstructions with physics-based alternatives. Data-consistency layers can enforce agreement with measured projections, while self-supervised training reduces dependence on clean labels. The model should not be judged only by peak signal-to-noise ratio. Task-based accuracy for a spacing, defect count, phase fraction, or inferred field is more meaningful; a blurrier reconstruction with honest uncertainty may be preferable to a sharp, overconfident image.

Table I. Representative roles of AI in modern physics and the corresponding validation burden.

Domain	Representative AI role	Principal opportunity	Dominant validation issue
Particle and nuclear physics	Event classification, detector reconstruction, fast simulation, likelihood-ratio estimation	Greater sensitivity and lower computing cost	Simulation-to-data mismatch and nuisance dependence
Astrophysics and climate	Transient classification, lens inference, gravitational-wave detection, learned forecasting	Rapid analysis of massive surveys and ensembles	Rare events, nonstationarity, and selection effects
Condensed matter and quantum physics	Phase recognition, neural quantum states, tomography	Compact representations of many-body structure	Ansatz bias and difficult out-of-distribution tests
Atomistic and materials research	Learned potentials, property prediction, inverse design	Larger simulations and accelerated candidate screening	Coverage of chemical space and experimental synthesizability
Fluids and fusion	Reduced models, learned closures, disruption prediction, control	Real-time prediction and optimization	Long-horizon stability and safety under shift
Scientific imaging	Denoising, segmentation, reconstruction, autonomous acquisition	Lower dose, higher throughput, adaptive measurement	Hallucination and loss of evidential traceability

IV. Opportunities for The Next Generation of Physics Research

A. Surrogate models, inverse design, and differentiable science

Many physical investigations are constrained not by a lack of governing equations but by the cost of evaluating them repeatedly. Learned surrogates can replace selected expensive modules inside Bayesian inference, uncertainty propagation, design optimization, and real-time control. Their advantage is greatest when a family of related computations must be performed and when the cost of generating training data can be amortized. Differentiable surrogates also provide gradients with respect to design variables, enabling inverse problems that would be cumbersome with a black-box simulator. The appropriate standard is end-to-end: time spent constructing, validating, and updating the surrogate must be counted, and the final physical decision must remain stable under its approximation error.

Inverse design reverses the conventional sequence from structure to property. A generative model proposes structures, fields, or experimental settings predicted to satisfy a target response. This can illuminate trade spaces that are difficult to search manually, including photonic structures, metamaterials, catalysts, and magnetic configurations. Constraints are crucial. A design that violates fabrication tolerances or relies on an unmodeled material response is not a solution. The best systems integrate manufacturability, robustness, and uncertainty into the objective, then return a diverse set of candidates rather than a single numerically optimal point.

B. Autonomous and closed-loop laboratories

Autonomous laboratories couple planning algorithms, robotic execution, measurement, and model updating. Reviews of self-driving laboratories describe the shift from automation of a fixed protocol to adaptive selection of the next experiment.²⁸ A mobile robotic chemist has demonstrated

autonomous navigation and experimental search in a laboratory environment.²⁹ In a more specialized physics-adjacent setting, closed-loop experimentation has accelerated the discovery of laser emitters by combining automated synthesis, characterization, and Bayesian decision making.³⁰ These platforms can reduce idle time and explore parameter spaces that are too large for manual campaigns.

The scientific promise is not simply faster throughput. Closed-loop systems can quantify why an experiment was selected, update uncertainty after a result, and expose the opportunity cost of alternative measurements. They may also reduce confirmation bias by testing surprising regions. Yet autonomy can concentrate systematic error: a miscalibrated instrument or misspecified acquisition function may steer hundreds of experiments in the wrong direction. Human oversight should therefore focus on model criticism, calibration, and intervention rules rather than approving every routine action. In laboratory, the system also needs practical competence - handling failed runs, contaminated samples, missing metadata, and instruments that behave differently on Monday morning.

C. Machine-assisted discovery of concepts and equations

Symbolic regression seeks compact mathematical expressions that fit data, potentially recovering conservation relations or effective laws. The work of Schmidt and Lipson showed that automated search could identify nonlinear dynamical relationships without a supplied equation template.³¹ AI Feynman combined dimensional analysis, separability, and neural approximation to recover symbolic expressions from benchmark data.³² Graph-based symbolic models have also been used to learn interpretable relations in astrophysical and dynamical systems.³³ These methods are attractive because the output can be inspected, differentiated, and compared with limiting theory.

A fitted equation is not automatically a physical law. Multiple expressions may be observationally indistinguishable over the available range, and symbolic search can exploit noise or hidden preprocessing. Discovery claims need dimensional checks, stability across resampling, tests on interventions or new regimes, and comparison with null models. The most productive use may be as a hypothesis generator that directs theoretical attention. It can reveal a compact regularity that a physicist then explains, derives, or rejects. That division of labor preserves the difference between detecting a pattern and understanding why it should hold.

D. Foundation models and multimodal scientific representations

Foundation models are trained on broad data and adapted to many downstream tasks. In physics, possible inputs include atomic structures, simulation trajectories, spectra, equations, code, images, and scientific text. Materials studies have already shown that transfer learning can help identify superconducting compounds and relate sparse experimental records to larger computed databases.³⁴ A multimodal model could connect a paper's textual description to its synthesis conditions, crystal structure, and measured response, making fragmented knowledge more queryable.

Scale creates opportunity but also obscures provenance. Scientific databases combine measurements made with different instruments, theoretical calculations at different fidelity, and text that may report only successful outcomes. Pretraining can smooth over these distinctions. Recent perspectives on materials foundation models consequently emphasize evaluation, data governance, and the need to connect general representations to experimentally relevant tasks.³⁵ Natural-language interfaces may improve access to simulation and instrumentation, but they can also produce fluent, unverified instructions. A language model should not be allowed to turn an ambiguous request into an irreversible experimental action without typed constraints and independent checks.

V. Future Challenges

A. Generalization, extrapolation, and scientific distribution shift

Physics often cares most about regimes that are rare, extreme, or not yet observed. Machine learning, by contrast, is strongest near the distribution represented in training. Random train-test splits can conceal this tension because neighboring points in a simulation campaign, time series, or composition family are strongly correlated. A rigorous benchmark should separate by physical regime: a new detector period, lattice size, Reynolds number, chemical family, phase, or forcing

condition. It should also distinguish interpolation from extrapolation rather than combining them into one average score.

Physics-informed constraints do not remove the problem. PINNs can exhibit severe optimization and conditioning failures even for equations that conventional solvers handle reliably, particularly when the loss contains competing scales or sharp features.³⁶ Neural operators can extrapolate poorly to resolutions or parameter ranges outside training. Learned potentials may become unstable during molecular dynamics. The correct response is not to abandon these methods but to design diagnostic tests around their use. Residual evaluation, conservation monitoring, uncertainty-triggered fallback, and comparison with low-fidelity solvers can prevent a local approximation from silently becoming a global claim.

Nonstationarity creates a related challenge. Instruments age, calibration changes, operating procedures evolve, and the climate distribution shifts. A model deployed for several years is not the same object that was validated at publication. Continuous monitoring is required, but continual retraining can itself alter the analysis and complicate reproducibility. Versioned models, frozen reference evaluations, and explicit criteria for retraining are therefore part of scientific methodology, not mere software maintenance.

B. Uncertainty, calibration, and model discrepancy

Scientific decisions require more than point predictions. Aleatoric uncertainty describes variability inherent in observations; epistemic uncertainty reflects limited knowledge of model parameters or structure; and model discrepancy captures the mismatch between the assumed generative process and reality. Neural ensembles, Bayesian approximations, conformal methods, and probabilistic networks can estimate parts of this uncertainty, but their calibration often deteriorates under shift. A uncertainty-aware workflow should ask whether uncertainty grows in unfamiliar regions and whether nominal coverage remains valid for the physical quantity of interest.

The separation between surrogate error and physical uncertainty is especially important. Suppose a learned emulator approximates a nuclear model inside a Bayesian analysis. Treating the emulator as exact can narrow the posterior. Inflating all predictions by a constant error may be equally misleading because approximation quality varies across parameter space. Better approaches model correlated emulator residuals and validate them at held-out design points selected to stress the posterior region.

Calibration can conflict with decision utility. A model may be globally calibrated but dangerously overconfident for a rare class, such as an impending disruption or an exotic detector signature. Risk-sensitive evaluation should weight the cost of failure, not only frequency. For high-consequence applications, abstention is a capability. A model that refuses an unfamiliar case and receives a slower trusted analysis may be more useful than one that always returns an answer.

C. Interpretability, causality, and the status of explanation

Feature attribution, saliency maps, latent-space probes, and concept-based explanations can reveal what a model responds to, but they do not necessarily establish a causal mechanism. Attribution methods can be unstable, and a visually persuasive heat map may reflect the behavior of the explanation algorithm as much as the predictive model. Physics offers stronger tests: controlled perturbations, symmetry transformations, counterfactual simulations, and comparison with known response functions. Explanations should be falsifiable. If a claimed feature matters, changing it while holding relevant confounders fixed should alter the prediction in a predictable way.

Causal inference is difficult because many physical data sets are observational and selection-biased. Simulations provide interventions, but only within the assumptions of the simulator. Combining causal graphs with mechanistic models and experimental design is a promising direction, particularly where active measurements can distinguish competing hypotheses. Still, causal language should be used carefully. A network that predicts a phase label from a correlation pattern has not shown that the correlation causes the phase.

The social meaning of explanation varies. An accelerator operator needs actionable indicators and a safe control envelope; a theorist may want a compact equation; an experimentalist may need to know whether a reconstruction invents spatial frequencies. No single score serves all audiences. The model are not neutral instruments, and its explanation requirements should be specified at the start.

D. Reproducibility, data quality, and computational cost

Reproducibility requires more than releasing network weights. A scientific result can depend on preprocessing, data exclusions, simulation versions, random seeds, numerical precision, hardware kernels, and hyperparameter search. Documentation should include a machine-readable description of the full pipeline and the exact model used for each reported figure. Independent replication on a physically distinct data set is more informative than rerunning the same code. Benchmark suites should include negative controls and hidden test cases to discourage tuning against public labels.

Data quality is often the binding constraint. Physics databases inherit instrument artifacts, uneven metadata, publication bias, and inconsistent conventions. Automated extraction from literature can amplify typographical errors or detach values from measurement conditions. The growing interest in materials and scientific foundation models makes curation, licensing, and provenance increasingly important.³⁷ A larger corpus may produce a better language model while producing a worse scientific database if contradictory measurements and theoretical predictions are merged without labels.

Computation also carries material cost. Training a large model consumes energy, hardware time, and specialist labor, while generating high-fidelity simulation data can dominate the budget. Scientific value should be compared with these costs and with simpler baselines. A carefully designed Gaussian process or reduced-order model may outperform a large neural system when data are scarce and uncertainty is central. Fashion is not a metric. The footprint of repeated training should be reported when substantial.

E. Governance, security, and epistemic responsibility

As AI moves toward experimental control, governance becomes a technical requirement. Access permissions, action limits, audit logs, and emergency shutdown procedures should be designed into autonomous platforms. Models that generate code or instrument commands create new routes for accidental damage and cybersecurity failure. A natural-language instruction must be translated into a constrained, typed action and checked against equipment state. The system should record not only what it did but which model version, observation, and objective led to the decision.

Responsibility remains distributed among data producers, model developers, instrument teams, and authors. This complicates conventional attribution. If a model trained on community data suggests a candidate that is later synthesized, the scientific contribution includes curation, algorithm design, experimental judgment, and validation. Transparent contribution statements can reduce the temptation to portray the AI as an autonomous discoverer while making human labor invisible.

Epistemic responsibility concerns the claims that researchers permit a model to support. A benchmark improvement is not automatically a physical insight; a simulation-trained posterior is conditional on the simulator; an autonomous experiment is not independent of its acquisition objective. Papers should state these conditions prominently. Few errors are more damaging than converting uncertainty about a model into certainty about nature.

VI. A Research Agenda for Trustworthy Scientific AI

Progress should be organized around scientific capability rather than generic model scale. First, benchmarks must represent actual inference goals and include distribution shift, rare events, and uncertainty coverage. A weather model should be tested on extremes and changing climate regimes; an interatomic potential on reactions and defects; a detector model across calibration periods. Second, architectures should encode established structure while retaining mechanisms to diagnose broken assumptions. Equivariance, conservation, and differentiable solvers are useful only when their domains of validity are explicit.

Third, hybrid systems need formal interfaces. A learned module should expose uncertainty, units, valid parameter ranges, and version information to the rest of the workflow. This enables a conventional solver or human operator to reject its output. Standardized data formats and model cards adapted to scientific use could record training distributions, symmetries, simulator versions, and known failure modes. These records must be more than public-relations documents; they should be testable against archived artifacts.

Fourth, AI should be integrated with experimental design. Active learning can select observations that discriminate hypotheses or reduce uncertainty, but acquisition functions should account for systematic error, experimental cost, and safety. Closed-loop systems need deliberate pauses for recalibration and model criticism. The next experiment is not always the one with the largest predicted information gain; sometimes it is the control measurement that checks whether the apparatus is still telling the truth.

Finally, education in physics should treat machine learning as both a computational method and an object of scientific criticism. Students need facility with optimization and probabilistic modeling, but also with dimensional analysis, numerical stability, uncertainty, and experimental systematics. Collaboration between domain physicists, statisticians, computer scientists, and research software engineers is essential. The most consequential failures often occur at their interfaces: a label whose physical meaning is misunderstood, a simulator treated as reality, or a production model deployed without monitoring.

VII. Conclusion

Artificial intelligence has become a versatile instrument across modern physics. It improves classification and reconstruction, accelerates simulation and inference, represents quantum and atomistic systems, supports real-time control, and expands the search space of experiments and materials. Its most credible successes share a pattern: the task is clearly defined, physical structure is incorporated where appropriate, uncertainty is evaluated, and the result is checked against independent theory or measurement.

The future will not be decided by a contest between AI and traditional physics. It will be shaped by hybrid methods in which analytical reasoning, numerical simulation, experimental judgment, and learned representations constrain one another. Larger scientific models and autonomous laboratories may make discovery faster, but speed without traceability can magnify error. AI earns a durable role in physics when it does more than predict - when it helps produce claims whose assumptions, limits, and evidential path remain open to scrutiny.

References

1. G. Carleo, I. Cirac, K. Cranmer, L. Daudet, M. Schuld, N. Tishby, L. Vogt-Maranto, and L. Zdeborova, *Rev. Mod. Phys.* 91, 045002 (2019).
2. G. E. Karniadakis, I. G. Kevrekidis, L. Lu, P. Perdikaris, S. Wang, and L. Yang, *Nat. Rev. Phys.* 3, 422-440 (2021).
3. A. Radovic, M. Williams, D. Rousseau, M. Kagan, D. Bonacorsi, A. Himmel, A. Aurisano, K. Terao, and T. Wongjirad, *Nature* 560, 41-48 (2018).
4. K. Cranmer, J. Brehmer, and G. Louppe, *Proc. Natl. Acad. Sci. U.S.A.* 117, 30055-30062 (2020).
5. M. Raissi, P. Perdikaris, and G. E. Karniadakis, *J. Comput. Phys.* 378, 686-707 (2019).
6. S. L. Brunton, B. R. Noack, and P. Koumoutsakos, *Annu. Rev. Fluid Mech.* 52, 477-508 (2020).
7. D. Guest, K. Cranmer, and D. Whiteson, *Annu. Rev. Nucl. Part. Sci.* 68, 161-181 (2018).
8. P. Baldi, P. Sadowski, and D. Whiteson, *Nat. Commun.* 5, 4308 (2014).
9. L. de Oliveira, M. Kagan, L. Mackey, B. Nachman, and A. Schwartzman, *J. High Energy Phys.* 07, 069 (2016).
10. A. Boehnlein et al., *Rev. Mod. Phys.* 94, 031003 (2022).
11. D. George and E. A. Huerta, *Phys. Lett. B* 778, 64-70 (2018).
12. Y. D. Hezaveh, L. P. L. Vasseur, and P. J. Marshall, *Nature* 548, 555-557 (2017).
13. R. Lam et al., *Science* 382, 1416-1421 (2023).
14. K. Bi et al., *Nature* 619, 533-538 (2023).

15. J. Carrasquilla and R. G. Melko, Nat. Phys. 13, 431-434 (2017).
16. E. P. L. van Nieuwenburg, Y.-H. Liu, and S. D. Huber, Nat. Phys. 13, 435-439 (2017).
17. G. Torlai et al., Nat. Phys. 14, 447-450 (2018).
18. J. Behler and M. Parrinello, Phys. Rev. Lett. 98, 146401 (2007).
19. K. T. Schutt, H. E. Saucedo, P.-J. Kindermans, A. Tkatchenko, and K.-R. Muller, J. Chem. Phys. 148, 241722 (2018).
20. V. L. Deringer, M. A. Caro, and G. Csanyi, Adv. Mater. 31, 1902765 (2019).
21. D. Pfau, J. S. Spencer, A. G. D. G. Matthews, and W. M. C. Foulkes, Phys. Rev. Res. 2, 033429 (2020).
22. J. Hermann, Z. Schatzle, and F. Noe, Nat. Chem. 12, 891-897 (2020).
23. A. Merchant et al., Nature 624, 80-85 (2023).
24. I. Batatia et al., J. Chem. Phys. 163, 184110 (2025).
25. J. Kates-Harbeck, A. Svyatkovskiy, and W. Tang, Nature 568, 526-531 (2019).
26. J. Degraeve et al., Nature 602, 414-419 (2022).
27. J. M. Ede, Mach. Learn.: Sci. Technol. 2, 011004 (2021).
28. F. Hase, L. M. Roch, and A. Aspuru-Guzik, Trends Chem. 1, 282-291 (2019).
29. B. Burger et al., Nature 583, 237-241 (2020).
30. F. Strieth-Kalthoff et al., Science 384, eadk9227 (2024).
31. M. Schmidt and H. Lipson, Science 324, 81-85 (2009).
32. S.-M. Udrescu and M. Tegmark, Sci. Adv. 6, eaay2631 (2020).
33. M. Cranmer et al., Adv. Neural Inf. Process. Syst. 33, 17429-17442 (2020).
34. V. Stanev, K. Choudhary, A. G. Kusne, J. Paglione, and I. Takeuchi, Commun. Mater. 2, 105 (2021).
35. E. O. Pyzer-Knapp et al., npj Comput. Mater. 11, 61 (2025).
36. A. S. Krishnapriyan, A. Gholami, S. Zhe, R. M. Kirby, and M. W. Mahoney, Adv. Neural Inf. Process. Syst. 34, 26548-26560 (2021).
37. X. Jiang et al., npj Comput. Mater. 11, 79 (2025).

