IOSR Journal of Business and Management (IOSR-JBM)
e-ISSN:2278-487X, p-ISSN: 2319-7668. Volume 28, Issue 5. Ser. 2 (May. 2026), PP 99-104
www.iosrjournals.org

A Comparative Analysis of Health Expenditure Patterns among BRICS Nations With Special Reference to Digitalization and AI Adoption

Kaushik Das[1] and Dr. Priyabrata Panda[2*]
[1]*Research Scholar, Department of Commerce, Fakir Mohan University, Balasore, Odisha, India*
[2]*Assistant Professor of Commerce, Gangadhar Meher University, Amruta Vihar, Sambalpur, Odisha, India*
[*]*Corresponding author*

Abstract
The study measures the impact of digitalization and AI adoption on the health expenditure of BRICS nations. The research work also compares the health expenditure pattern of the nations. Health expenditure to GDP and the current health expenditure have been taken for such a purpose. The data from 2000 to 2025 has been taken, and t-test and ANOVA have been applied for such purpose. It is found that AI and digitalization adoption have a significant impact on the health expenditure of the countries. The health expenditure patterns of the countries are also different from each other. Their health policy and strategy is not affected by the trade block, but rather by many disruptive dynamics.
Keywords: *BRICS Nations, Healthcare Expenditure, Digitalization, and AI adoption.*

I. Introduction

Good physical and mental well-being is more valuable than money; that's why we say "Health is wealth". During the last 10 years, public health expenditure has increased significantly all over the world, including in the BRICS nations. An increase in healthcare expenditure has positive health and other allied outcomes (Singh et al. 2025), which leads to economic development of the nations. BRICS nations have a significant contribution towards global GDP in purchasing power parity (PPP), which is near about 40%. Increased spending and technological innovation are changing healthcare systems across BRICS countries. There has been a significant development in recent years in the healthcare sector after the integration of Artificial Intelligence. AI technologies have a significant implication in the areas of the healthcare sector, such as disease diagnosis, medical imaging analysis, drug discovery, telemedicine, and hospital management systems. The integration of AI in healthcare settings can provide automation of tasks, predictive analytics, and decision-making support, and with these improvements, organisations will deliver healthcare faster, with better quality, and at a lower cost(Khanijahani et al. 2022). AI-based diagnostic tools help healthcare professionals to identify different diseases at earlier stages. Governance factor has been pivotal in the adoption of AI in the health sector(Hassan et al. 2024). Use of AI in healthcare enhances decision-making and improves diagnostic accuracy and efficiency. Physicians with AI assistance perform better than those who rely on only conventional tools, still there is no evidence of advantages of time efficiency in case completion by using AI assistance.

II. Review of Literature

Healthcare Expenditure, Health Outcomes, and Sustainable Development

With many other contributors, increased health expenditure is an important factor positively impacting sustainable development (Bala, 2026; Liu, 2026). It is also found that there is a long-run cointegration among health expenditure, trade openness and health indicators of BRICS nations(Mehta & Derbeneva, 2025). An increase in the number of health professionals has a positive impact on the reduction in child mortality in rural China (Liang et al., 2019). There is a significant decline in under-5-year-old (U5) child death and infant death, for every per capita increase of health expenditure in India (Sridevi & Laxmaiah, 2020) and a positive relationship between per capita health expenditure and health output of the country (Saji & Madheswaran (2025)). However, Singh et al. (2025) noticed that despite an increase in healthcare expenditure, there is no significant & satisfactory health outcome in Central Europe and Baltic (CUB) countries. In addition, Bulut and Altintaş (2025) found that GDP has a weak direct relation to health outcomes. Similarly, it is deduced that there is no evidence that public health expenditure reduces private expenditure(Das, 2017).

But there is a significant association between participatory governance and health outcomes, specifically, mitigating HIV/AIDS (Touchton et al., 2024). Suggesting that policymakers should prioritise public health investment to foster economic growth (Kaur 2023). Tigga and Sarkar (2025) substantiated that an efficient utilisation of resources and adoption of technology can reduce health expenditure.

Digitalisation and AI Adoption in Healthcare

Artificial Intelligence (AI) is increasingly renovating healthcare by enhancing diagnostic accuracy, efficiency, and decision-making. (Topol, 2019) highlighted the potential of AI to transform medicine through precision diagnostics and personalized treatment. (Jiang et al. 2017) have demonstrated the core application of AI in various disease diagnoses and also in clinical decision support systems. Similarly, (Esteva et al. 2017) showed that through deep learning models early detection of skin cancer can improve survival rates and can outperform dermatologists in skin cancer detection. AI adoption has significantly upgraded in healthcare efficiency and patient outcomes. (Rajkomar, Dean, and Kohane 2019) emphasised AI's role in predictive analytics and early disease detection, and also highlights that machine learning has not yet significantly influenced healthcare, despite its potential to process vast clinical data beyond human comprehension. (Obermeyer and Emanuel 2016) discussed the process, how machine learning can enhance clinical decision-making and resource allocation. (Davenport and Kalakota 2019) highlighted AI's ability in cost reduction and improved administrative efficiency in healthcare systems. In terms of patient care, (Bates et al. 2014) and (Krittanawong et al. 2017) demonstrated that AI tools improve patient monitoring and minimise medical errors. (Davoudi et al. 2018) explored applications of deep learning using electronic health records, which enhance treatment outcomes. (Gulshan et al. 2016) demonstrated the effectiveness of AI's detection in the area of diabetic retinopathy with high accuracy. Despite its several benefits, AI adoption faces a lot of challenges. (He et al. 2019; Kelly et al. 2019) identified issues such as data privacy, lack of transparency, and regulatory concerns. (WHO, 2021) emphasised the importance of ethical considerations and governance frameworks for AI in the healthcare sector. (Reddy et al. 2020) pointed out the digital divide and infrastructure lacunas in developing countries. (Acemoglu and Restrepo 2020) also discussed the wider implications of automation, including workforce displacement. Overall, the literature suggests that AI adoption enhances healthcare efficiency, accuracy, and accessibility, but its success depends on addressing ethical, infrastructural, and regulatory challenges.

III. Objectives of the Study

The paper compares the health expenditures among the BRICS country. The health expenditure to GDP is taken as the variable for such purpose. The research work also assesses the impact of digitalisation and AI adoption in health sector expenditure of the nations.

IV. Research Methodology

In this study secondary data is used for analysis according to the objectives of the research paper. There are two dependent variables i.e. Health expenditure to % of GDP and total Current health expenditure which includes domestic private health expenditure, domestic general government health expenditure and external health expenditure collected from World Health Organization (WHO) published data. Data have been collected for 26 years from 2000 to 2025. For data analysis, MANOVA (Multivariate Analysis of Variance) is used to test differences across groups on multiple dependent variables, such as Health expenditure to % of GDP and total Current health expenditure.

A pre and post-comparison is also made, making a break point on the basis of digitalisation and AI adoption in different countries. The break point with the logic is mentioned below:

Table 1: Break Points for digitalisation and AI adoption with reasons

Country	Pre-Period	Post-Period	Reason (AI & Digitalisation Breakpoint)
Brazil	2000–2019	2020–2025	The COVID pandemic forced the adoption of telemedicine and digital health platforms
Russia	2000–2016	2017–2025	The Digital Economy Program adopted digital health initiatives
China	2000–2015	2016–2025	The "Healthy China 2030" campaign has promoted AI and big data in healthcare
South Africa	2000–2018	2019–2025	Promotion of the national e-health initiatives and digital health systems
India	2000–2016	2017–2025	National Health Policy 2017 and push toward digital health ecosystem

Source: Compiled

V. Data Analysis

Table 2: Levene's Test of Homogeneity

Variables/Parameters		Levene Statistic	df1	df2	Sig.
HE_GDP	Based on Mean	1.705	4	121	.153
	Based on Median	1.577	4	121	.185
	Based on Median and with adjusted df	1.577	4	98.57	.186
	Based on trimmed mean	1.720	4	121	.150
CHE	Based on Mean	1.471	4	121	.215

	Based on Median	1.256	4	121	.291
	Based on Median and with adjusted df	1.256	4	111.7	.291
	Based on trimmed mean	1.453	4	121	.221

Source: Data compiled in SPSS
Che= current health expenditure
HE_GDP= health expenditure to percentage of GDP

The test above replicates the following hypotheses:
H_0: Groups are homogeneous
H_1: Groups are not homogeneous
Analysis: in this study Levene's test have used to examine the assumption of homogeneity of variances across groups. On health expenditure as a percentage of GDP, the Significant value based on mean is (p = 0.153), median is (p = 0.185), adjusted median is (p = 0.186), and trimmed mean is (p = 0.150), all of which were greater than 0.05. which indicates that groups are homogeneous. Similarly, we analysed current health expenditure, where the significance values based on mean (p = 0.215), median (p = 0.291), adjusted median (p = 0.291), and trimmed mean (p = 0.221). All these p-values exceed 0.05, which indicates the rejection of the null hypothesis by confirming homogeneity of variance across countries for current health expenditure (CHE) as % of Gross Domestic Product (GDP) and total current health expenditure.

Table 3: Comparison of Health Expenditure

Source	Dependent Variable	Type III Sum of Squares	df	F	Sig.
Corrected Model	HE[a]	14.903[a]	4	257.821	.000
	CHE[b]	138.987[b]	4	49.001	.000
Intercept	HE	377.832	1	26146.4	.000
	CHE	24306.494	1	34277.83	.000
Country	HE	14.903	4	257.821	.000
	CHE	138.987	4	49.001	.000
Error	HE	1.749	121		
	CHE	85.801	121		
Total	HE	397.123	126		
	CHE	24558.329	126		
Corrected Total	HE	16.651	125		
	CHE	224.788	125		

Source: Compiled
Note: [a]R Squared = .895 (Adjusted R Squared = .892); [b]R Squared = .618 (Adjusted R Squared = .606); HE: Health Expenditure to GDP and CHE: Current Health Expenditure

The table reveals the Anova result for comparison of health expenditure and health expenditure to GDP of BRICS countries with a null hypothesis that there is no significant difference in health expenditure pattern of the countries. As the null hypothesis is rejected at 1% level deducing a difference in health expenditure pattern among the nations.

Table 4: Post-hoc multiple comparisons (Tukey HSD)

Dependent Variable	(I) Country	(J) Country	Mean Difference (I-J)	Std. Error	Sig.
HE_GDP	Brazil	Russia	.4979*	.03482	.000
		India	.9227*	.03334	.000
		Chinna	.6211*	.03334	.000
		SA	.1058*	.03334	.016
	Russia	Brazil	-.4979*	.03482	.000
		India	.4249*	.03482	.000
		Chinna	.1233*	.03482	.005
		SA	-.3921*	.03482	.000
	India	Brazil	-.9227*	.03334	.000
		Russia	-.4249*	.03482	.000
		Chinna	-.3016*	.03334	.000
		SA	-.8169*	.03334	.000
	Chinna	Brazil	-.6211*	.03334	.000
		Russia	-.1233*	.03482	.005
		India	.3016*	.03334	.000
		SA	-.5153*	.03334	.000
	SA	Brazil	-.1058*	.03334	.016
		Russia	.3921*	.03482	.000
		India	.8169*	.03334	.000
		Chinna	.5153*	.03334	.000

CHE	Brazil	Russia	-1.8051*	.24394	.000
		India	-2.1605*	.23355	.000
		Chinna	-1.7596*	.23355	.000
		SA	.3726	.23355	.503
	Russia	Brazil	1.8051*	.24394	.000
		India	-.3554	.24394	.592
		Chinna	.0455	.24394	1.000
		SA	2.1778*	.24394	.000
	India	Brazil	2.1605*	.23355	.000
		Russia	.3554	.24394	.592
		Chinna	.4008	.23355	.428
		SA	2.5331*	.23355	.000
	Chinna	Brazil	1.7596*	.23355	.000
		Russia	-.0455	.24394	1.000
		India	-.4008	.23355	.428
		SA	2.1323*	.23355	.000
	SA	Brazil	-.3726	.23355	.503
		Russia	-2.1778*	.24394	.000
		India	-2.5331*	.23355	.000
		Chinna	-2.1323*	.23355	.000

Source: Data compiled in SPSS

The Tukey HSD post-hoc test have used to examine pairwise differences among BRICS countries. There are two dependent variables were analyzed: Health Expenditure to GDP and total Current Health Expenditure (CHE). For HE to % of GDP, is significant at the 5% level in almost all country comparisons were statistically significant. This indicates substantial variation in overall health expenditure to GDP across countries. Brazil shows significantly higher HE to % of GDP compared to all other nations on the other hand India records significantly lower HE to GDP than Brazil, Russia, China, and South Africa. Russia and China also differ significantly, though the gap is smaller. It is found that South Africa shows moderate but significant differences with most countries. The confidence intervals for HE to % of GDP comparisons do not include zero, confirming robustness. Overall, HE to % of GDP reflects strong inequality in healthcare investment among BRICS nations. For CHE, fewer pairwise differences are statistically significant. This suggests relatively lower variation in current healthcare spending. No significant difference is found between Russia and India. Russia and China also show no significant difference in CHE. India and China exhibit statistically similar CHE levels. Brazil and South Africa also do not differ significantly in CHE. However, Brazil differs significantly from India, Russia, and China. South Africa shows significant differences with Russia, India, and China. These findings indicate partial convergence in current health expenditure. Overall, while HE to % of GDP shows wide disparities, CHE reflects more similarity across BRICS countries.

Table 5: Impact of Digitalisation and Ai Adoption on Health Expenditure

Countries	t-stat (P value)	Impact of Digitalisation and AI Adoption
Brazil	-4.91 (0.00)	Significant impact at 1% level
Russia	4.72 (0.00)	Significant impact at 1% level
India	4.02 (0.02)	Significant impact at 5% level
China	-8.45 (0.00)	Significant impact at 1% level
South Africa	-6.98 (0.00)	Significant impact at 1% level

Source: Compiled

The table above reveals the impact of digitalisation and AI adoption on health expenditure. Such an impact is significant, and well felt for all the BRICS countries at 1% level and for India at 5% level.

VI. Implication and Conclusion

The health expenditure patterns of the BRICS countries is significantly different from each other. Though the countries are allied in a trade block, their demography, consumption, revenue generation, democracy and geography are different, leading to different types of health policy and health budget. They rely on diverse dynamics but focus on large expansion with research, innovation and AI adoption. The countries struggle with equity, equality, and resource allocation. India and China made significant expenditures on public health infrastructure, while South Africa tried to reduce inequalities. Brazil puts emphasis on a universal healthcare system while Russia stresses state-funded services. The countries have implemented massive initiatives, campaigns and strategies for digitalisation and AI adoption to execute health plans and policies.

References

Bala, M. M. (2026). Inequality, development, and the environment: Determinants of health outcomes in Sub-Saharan Africa. *Sustainable Development*. https://doi.org/10.1002/sd.70666

Bates, D. W., Saria, S., Ohno-Machado, L., Shah, A., & Escobar, G. (2014). Big data in health care: Using analytics to identify and manage high-risk and high-cost patients. *Health Affairs, 33*(7), 1123–1131.

Bulut, C., & Altintaş, T. (2025). The effects of health expenditures on socioeconomic indicators and health status: A canonical correlation analysis. *Archives of Health Science and Research, 12*(1). https://doi.org/10.5152/ArcHealthSciRes.2025.25030

Cardoso, L. B., Souza, K. B. de, Santiago, F. S., Venson, A. H., & Rosa, M. V. G. (2025). Macroeconomic effects of sugar-sweetened beverages taxation: Simulations in a computable general equilibrium model for Brazil. *Quality & Quantity, 59*(2), 1235–1255. https://doi.org/10.1007/s11135-024-02014-5

Das, D. (2017). Public expenditure and healthcare utilization: The case of reproductive health care in India. *International Journal of Health Economics and Management, 17*(4), 473–494. https://doi.org/10.1007/s10754-017-9219-7

Davenport, T., & Kalakota, R. (2019). The potential for artificial intelligence in healthcare. *Future Healthcare Journal, 6*(2), 94–98.

Davoudi, A., Malhotra, K. R., Shickel, B., Siegel, S., Williams, S., Ruppert, M., & Rashidi, P. (2018). The intelligent ICU pilot study: Using artificial intelligence technology for autonomous patient monitoring. *arXiv preprint arXiv:1804.10201*.

Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017). Dermatologist-level classification of skin cancer. *Nature, 542*(7639), 115–118.

Goldberg, J. S. (2023). What we measure when we measure the effects of user fees: A replication, reanalysis, and extension of Tanaka (2014). *Empirical Economics, 65*(4), 1981–2009. https://doi.org/10.1007/s00181-023-02400-2

Gupta, I., & Mitra, A. (2004). Economic growth, health and poverty: An exploratory study for India. *Development Policy Review, 22*(2), 193–206. https://doi.org/10.1111/j.1467-7679.2004.00245.x

Gulshan, V., Peng, L., Coram, M., et al. (2016). Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. *JAMA, 316*(22), 2402–2410. https://doi.org/10.1001/jama.2016.17216

Haojie, D., Lei, Y., & Bhattacharya, T. (2025). Combined impact of Chinese exercise and electrotherapy on improving range of motion in anterior cruciate ligament (ACL) injury patients. *International Journal of Human Movement and Sports Sciences, 13*(1), 10–20. https://doi.org/10.13189/saj.2025.130102

Hassan, S. A., Zaman, K., Zaman, S., & Shabir, M. (2014). Measuring health expenditures and outcomes in SAARC region: Health is a luxury? *Quality & Quantity, 48*(3), 1421–1437.

He, J., Baxter, S. L., Xu, J., Xu, J., Zhou, X., & Zhang, K. (2019). The practical implementation of artificial intelligence technologies in medicine. *Nature Medicine, 25*(1), 30–36.

Jiang, F., Jiang, Y., Zhi, H., Dong, Y., Li, H., Ma, S., et al. (2017). Artificial intelligence in healthcare: Past, present and future. *Stroke and Vascular Neurology, 2*(4), 230–243.

Kaur, A. (2023). Health status, government health expenditure and economic growth nexus in India: A Toda–Yamamoto causality approach. *Arthaniti: Journal of Economic Theory and Practice, 22*(1), 34–46.

Kaur, S., Kiran, R., & Sharma, R. (2024). Healthcare expenditure, health outcomes and economic growth: A study of BRICS countries. *Millennial Asia*.

Kelly, C. J., Karthikesalingam, A., Suleyman, M., Corrado, G., & King, D. (2019). Key challenges for delivering clinical impact with artificial intelligence. *BMC Medicine, 17*(1), 195.

Khanijahani, A., Iezadi, S., Dudley, S., Goettler, M., & Kroetsch, P. (2022). Organizational, professional, and patient characteristics associated with artificial intelligence adoption in healthcare: A systematic review.

Krittanawong, C., Zhang, H., Wang, Z., Aydar, M., & Kitai, T. (2017). Artificial intelligence in precision cardiovascular medicine. *Journal of the American College of Cardiology, 69*(21), 2657–2664.

Liang, S., Macinko, J., Yue, D., & Meng, Q. (2019). The impact of the health care workforce on under-five mortality in rural China. *Human Resources for Health, 17*(1).

Liu, Y. (2026). Analyzing tourism sector's influence on sustainable development, ecological sustainability, profitability, and employability in China. *Sustainable Development*.

Mall, S., Panigrahi, T. R., & Kabir Hassan, M. (2024). Neo banking: A bibliometric review of the current research trend and future scope. *International Review of Economics and Finance, 96*.

Mehta, D., & Derbeneva, V. V. (2025). The asymmetric impact of health expenditure, bottom decile income, and trade openness on BRICS health indicators. *Economy of Regions, 21*(2), 394–411.

Obermeyer, Z., & Emanuel, E. J. (2016). Predicting the future—Big data, machine learning, and clinical medicine. *New England Journal of Medicine, 375*(13), 1216.

Rajkomar, A., Dean, J., & Kohane, I. (2019). Machine learning in medicine. *New England Journal of Medicine, 380*(14), 1347–1358.

Reddy, S., Allan, S., Coghlan, S., & Cooper, P. (2020). A governance model for the application of AI in health care. *Journal of the American Medical Informatics Association, 27*(3), 491–497.

Ruan, X., Li, K., Yang, M., Dong, Z., & Wang, G. (2024). From China to the world: The implications of fiscal decentralization, government debt, and public health dynamics. *Environment, Development and Sustainability*.

Saji, D. R., & Madheswaran, S. (2025). Public expenditure efficiency on health in Indian states: Generalised stochastic frontier approach. *Journal of the Asia Pacific Economy*.

Sebayang, T. E., Hakim, D. B., Bakhtiar, T., & Indrawan, D. (2024). What accelerates the choice of mobile banking for digital banks in Indonesia? *Journal of Risk and Financial Management, 17*(1).

Shickel, B., Tighe, P. J., Bihorac, A., & Rashidi, P. (2018). Deep learning in healthcare. *Journal of Biomedical Informatics, 83*, 113–124.

Singh, S., Jain, R. U., & Kumar, N. (2025). Convergence of health expenditure and health outcomes in Central Europe and the Baltic region. *Eastern European Economics, 63*(1), 111–124.

Sridevi, M., & Laxmaiah, A. (2020). Healthcare financing and under-5 child mortality among the BRICS nations. *Indian Journal of Human Development, 14*(3), 507–517.

Tigga, N. S., & Sarkar, P. (2025). Has the efficiency and productivity of the health system in India improved during post-policy period? *Applied Economics, 57*(11), 1239–1256.

Topol, E. (2019). *Deep medicine: How artificial intelligence can make healthcare human again*. Hachette UK.

Touchton, M., Borges, N., & Wampler, S. B. (2024). Participatory health governance and HIV/AIDS in Brazil. *Latin American Politics and Society, 66*(1), 158–177.

Wang, H., Ma, G., & Lu, H. (2025). Determinants of equitable public health human resource allocation in China. *Human Resources for Health, 23*(1).

World Health Organization. (2021). *Ethics and governance of artificial intelligence for health*. WHO Press.

Xie, Z., Deng, W., Liang, Z., Xie, Y., Chen, J., & Cao, W. (2025). Cost-effectiveness of once-weekly insulin icodec versus daily basal insulins. *ClinicoEconomics and Outcomes Research, 17*, 771–787.

Zhang, J., Yin, C., Li, H., Wei, W., Gong, Y., & Tang, F. (2020). Application of self-reported ACT questionnaire in asthma management. *Patient Preference and Adherence, 14*, 1027–1036.