Journal of Economics, Finance and Accounting Studies
ISSN: 2709-0809
DOI: 10.32996/jefas
Journal Homepage: www.al-kindipublisher.com/index.php/jefas

JEFAS
AL-KINDI CENTER FOR RESEARCH AND DEVELOPMENT

| RESEARCH ARTICLE

AI-Driven forecasting in BRICS infrastructure investment: impacts on resource allocation and project delivery

Md Sohanur Rahman Sourav[1], Arafat Hossain[2], Md Redwanul Islam[3], Mohtasim Wasif[4], Sujana Samia[5]✉

[1]*Master of Science in Administration in Project Management, Central Michigan University, Michigan, USA*
[2]*MBA in Business Analytics, International American University, California, USA*
[3]*Department of Finance & Financial Analytics, University of New Haven, West Haven, CT, USA*
[4]*MBA in Project Management, Central Michigan University, Hamtramck, Michigan, USA*
[5]*Department of Business Analytics, Trine University, Detroit, Michigan, USA*
Corresponding Author: Sujana Samia, **E-mail**: sujanasamia26@gmail.com

| ABSTRACT
This study explores the role of artificial intelligence (AI)-driven forecasting in improving resource allocation, cost prediction, and project delivery in infrastructure investment within the BRICS nations (Brazil, Russia, India, China, South Africa). Through an analysis of 100 infrastructure projects, the study evaluates the effectiveness of AI tools in addressing common challenges such as cost overruns, project delays, and inefficient resource utilization. Using machine learning models, optimization algorithms, and predictive analytics, the study demonstrates that AI can significantly enhance cost prediction accuracy, reduce project completion time deviations, and optimize resource allocation, resulting in overall cost savings. The results show an average prediction error of 5.00% for cost forecasts and a 5.42% deviation in project timelines. AI-driven optimization led to an average cost saving of 5.45%. Additionally, AI tools identified 25% more risks compared to traditional methods, contributing to more proactive risk management. However, the study also highlights the challenges of implementing AI in countries with varying levels of technological readiness, data quality, and organizational resistance. The findings suggest that AI can play a critical role in transforming infrastructure development in BRICS nations, provided that barriers to adoption are addressed.

| KEYWORDS
AI-driven forecasting, infrastructure investment, resource allocation, cost prediction, project delivery, BRICS nations, machine learning, risk mitigation, optimization algorithms, predictive analytics.

| ARTICLE INFORMATION

ACCEPTED: 15 March 2025 **PUBLISHED:** 03 April 2025 **DOI:** 10.32996/jefas.2025.7.2.11

1. Introduction

1.1 Background and Context
Investing in infrastructure has been a well understood fact of economic development over the decades, especially for developing economies. The BRICS nations—Brazil, Russia, India, China, and South Africa—represent some of the largest and most dynamic emerging markets in the world (Stuenkel, 2020). Today, the expanding populations and urbanization associated with rapid economic growth and the evolving industrial sector in these countries make the need for this significant investment in infrastructure higher than ever. Infrastructure easing of connectivity, productivity boost, and facilitating goods and services flow is very integral for the economic growth itself. Nonetheless, these BRICS nations often struggle with their infrastructural projects – especially with wasting of resources, delay, and cost overruns (Caswell, 2021). Often, these problems make it difficult to provide important infrastructure in a timely and cost-effective manner.

1.2 Problem Statement

Current methods of managing such infrastructure projects with conventional approaches e.g. expert judgment and historical data lack the ability to cope with the complex and uncertain process of large-scale infrastructure projects (Love et al., 2022). However, these methods are not well suited to give accurate predictions about costs, timelines and the allocation of resources if those are affected by external factors, for e.g. fluctuating resource prices and political instability. With these challenges in mind, there is a strong case based on the need for more advanced tools and techniques to assist the forecasting and management of infrastructure projects (Al-Raeei, 2025). One of the best answers is to use artificial intelligence (AI), which helps to significantly improve forecasting accuracy, optimizes resource allocation and minimizes risks of infrastructure development.

1.3 Research Motivation

There is potential in changing the way infrastructure is invested by means of the usage of data driven insights via artificial intelligence. AI makes possible to analyze a great amount of data, detect models and predict results with human precision using techniques such as machine learning, predictive analytics, and optimization algorithms (Sarker, 2021). Resource demands can be forecasted through applying AI tools, materials, labor, and equipment can be optimized in their distribution, and potential projects risks can be identified at early stages of the project life cycle. Using these capabilities to determine exactly how planning can be made more accurate, this may be useful in making infrastructure projects in BRICS countries more efficient by achieving more reliable and on time delivery of projects, on budget. While there has been an increasing acceptance of what AI can do, its use in infrastructure investment is still quite limited and it has not found its way into the fold of the BRICS nations yet.

1.4 Research Objective

This study aims first to examine the use of AI based forecasting in investment into BRICS infrastructure. Moreover, the study will focus on the implications of the use of AI tools on resource allocation and project delivery and how these tools provide an opportunity to increase the accuracy of the cost estimation, decrease the delay as well as improve the resource efficiency. This research will give an insight about how the AI can be used to seek solutions to the common challenges of infrastructure projects in BRICS countries through assessment of the use of AI in selected case studies from BRICS countries.

1.5 Significance of the Study

There are several reasons for the significance of this research. Firstly, it will support the literature on AI applications in infrastructure management, focusing on the emerging economies (Mhlanga, 2021). As the majority of the existing research on AI in infrastructure has been applied in developed countries, very little is known about its usages in BRICS nations. This study will second, offer practical insights to policymakers, infrastructure developers and investors in these countries, to understand how AI may improve plan and management, as well as the execute and manage of infrastructure projects (Prasad et al., 2024). This research demonstrates how AI can optimize resource allocation and forecasting to bring efficiency and effectiveness in infrastructure development in BRICS countries so as to contribute to the economic and social development of the countries at a broader scale.

1.6 Structure of the Manuscript

In the Literature Review, firstly the literature on AI applications to infrastructure investment is reviewed and the issues that the BRICS countries face are highlighted. Through this will be derived the capability of AI to overcome these problems. In the Methodology section, it will describe the approach that the study has taken for this study including the data sources, AI tools and the case studies used for analysis. The Results will feature the results of the study on how AI forecast enhances resource allocation and project delivery for selected infrastructure projects. The results shall be interpreted and discussed along the broader implications of AI adoption in infrastructure investment in the Discussion section. Lastly, the Conclusion will wrap up the study with its key findings, make suggestions for future research, and propose policies for development.

2. Literature Review

2.1 AI in Infrastructure Investment

In recent years, artificial intelligence (AI) has grown in popularity for its disruptive effect on different industries and infrastructure investment is no exception. For example, traditional forecasting and management practices used in the past turn out to be inadequate for dealing with the intricacies of the estimation of cost, resource optimization, and risk management in the highly complex and rapidly evolving environment that arises in response to such global infrastructure needs. With the introduction of AI, the study unlocks the capacity to handle huge quantities of information rapidly, find out from patterns, and also forecast future end results like never before. A comprehensive review by Yigitcanlar et al. (2020) sheds light on the diverse applications of AI in infrastructure, particularly in smart city development. Having acquired knowledge about road constructions and intervention carried out along the infrastructures, their study focuses on how AI technologies like machine learning and data analytics have been utilized to improve urban infrastructure planning, design and management. AI will further aid cities to optimize traffic flow, energy distribution, waste management and even to allocate resources in real time in the areas of research it highlights. In addition, AI can also predict failures in the infrastructure systems to perform the maintenance proactively, which will reduce downtime and consequently the costs involved and improve efficiency.

Likewise, Hu et al. (2024) explores AI's role in the cost management of civil engineering projects with a process and a case study to analyze how AI techniques can enhance the predictability of the cost. Proposing a hybrid multi-criteria decision, they integrate the expert judgement with the AI driven forecasting models. The combination gives more reliable predictions that would make any budget overrun or project delay minimal. In particular, they explain how using AI to efficiently estimate construction costs through the analysis of historical data, market trends in the current stage, and project variables will lead to more accurate forecasting. Shkodinsky et al. (20244) discuss AI's involvement in figuring out technical risks, specifically in the realm of big infrastructure projects, which are subject to unforeseen difficulties that can cause major disruptions. What their work has focused on is how AI driven predictive models can predict possible risks that may not be apparent as an initiative is gearing up – supply chain disruption, for example, lack of labor, government regulation. These models can be incorporated in the project planning & execution process by the decision makers to implement mitigation strategies upfront thus decreasing the project risk and increasing their chances of delivering successful projects.

In complex systems engineering, Ekundayo (2024) extends the study of AI driven decision intelligence in, the construction and infrastructure sectors. The research underscores the benefit of data driven decision making when decisions are applicable for interdependent infrastructure systems where real time data is vital to stability. AI allows the combination of many sources of data such as construction schedules, available resources and financial data into a cohesive decision-making process. As a result, the project execution is optimized by reducing costs and completion times of the project.

2.2 Challenges in BRICS Infrastructure

AI has much promise for better infrastructure investment, yet the tasks that BRICS countries have in incorporating these technologies cannot be underestimated. Several obstacles confront the BRICS nations, a diverse group of political, economic, technological environments, in the management of large-scale infrastructure projects. Such challenges include budget overrun and delays, political instability and supply chain disruptions, and can make successful delivery of infrastructure projects harder. While Nach and Ncwadi (2024) in their article discuss challenges of economic integration for BRICS countries they point out how political instability and shifting economic factors sometimes stifle the development of infrastructure. Specifically, the research identifies that projects are completed far later than expected and that the costs to build them far exceed the budgets allocated — and argues that political instability compounds the delays and can make the project costs spiral out of control. For example, shifts in the political landscape can result in change of government policies and allocation of funds which translate into a lack of long-term planning for infrastructure in countries such as Brazil and South Africa.

The economic potential of BRICS countries has been discussed by Streltsov et al. (2021), but are accompanied by challenges that these countries are facing in modernizing their infrastructure. Among the challenges in the region that hinder the implementation of energy reliant technologies, are the lack of skilled labor, obsolescence of the technologies and insufficient funding for large infrastructure projects. The authors assert that the infrastructure development projects in BRICS nations have been making great strides but they have not been efficient enough, falling short because of poor management practices, political hurdles, and lack of use of available new technologies. In their paper, Gorbunova et al. (2020) focus primarily on systemic issues that arose on the BRICS infrastructure sector, including the requirement to establish a coordination mechanism that facilitates the overcoming of these barriers. They claim in that they analyzed that there is regulatory gap, different adoption rates of technology, different governmental support, which affects the inefficiency of infrastructure projects. This constrains standardizing and actualizing AI driven solution across these BRICS nations and thus restricts optimizing resource allocation and its improvement upon the project outcome.

2.3 Previous Studies on AI Forecasting

In recent years there has been a growing practice of applying AI forecasting in infrastructure investments, in particular, in BRICS countries. A number of studies have examined the capability of AI driven forecasting tool to improve the outcome of infrastructure projects through improved decision making and reduction of risks. The chapter by Abir et al. (2024) addresses the contribution of AI to the economic growth of economic growth of BRICS countries and in the specific applications of AI driven data analytics for better policy making and infrastructure planning. Advanced data analytics is necessary for projecting infrastructure demand which then can inform investment decisions. AI based prediction tools can determine the future need of infrastructure like demographic growth, pattern of urbanization and economic activity. That's why it is these tools can allow BRICS countries to make better use of available resources, and to invest in projects that fit in with future demand.

In Channe (2024), the impact of AI on the forecasting of taxes and prices is studied, as well as on policymaking in general, especially in developing countries. According to the research, AI based forecasting models can provide policy makers with insights to help them make more informed decisions, and this is useful when it comes to infrastructure investments in BRICS country. With AI tools, scholars can predict economic trends, evaluate development potential of infrastructure projects and redistribute resources in the best possible way, which contributes to more stable and sustainable development. The focus of Raghuvanshi et al. (2024) is the part of the role of AI in smart city development in the BRICS economies. By studying AI adoption and urban infrastructure, they discuss the opportunities and challenges of AI adoption in the urban infrastructure sector, providing discussion on how AI will make much more sense in planning and managing urban infrastructure. For instance, AI can manage the energy more efficiently; reduce the traffic congestion and increase the efficiency of waste management in the cities. All these make the cities be more efficient and sustainable. But there are also some obstacles standing in the way of AI adoption in BRICS countries, which include absence of technological infrastructure, lack of access to quality data and opposition from local authorities as well as industries.

2.4 Technology Adoption

There are multiple factors which have a determining role in the successful implementation of AI technologies in infrastructure projects, technological readiness being one of them, as well as government policy and industry practices. These factors must coincide for AI to be implemented into infrastructure development in a successful and useful way. Using the Technology-Organization-Environment (TOE) framework, Stenberg and Nilsson (2020) study the factors affecting the government authorities' adoption of AI technologies. The study discovers that while most BRICS countries have the technological potential for AI adoption, the challenge in organizational readiness, including lack of skilled personnel and inadequate infrastructure, prevents the proper deployment of the AI. Finally, these findings suggest that the efforts to overcome the barriers are intertwined and require a concerted effort of government, industry, and academia to encourage the infusion of knowledge in AI, supporting the development of the AI infrastructure, and enabling a supportive regulatory environment.

Akhter & Abir et al. (2024) examine the role of private investment in AI in promoting environmental sustainability in the United States, highlighting how AI-driven innovations contribute to optimizing resource utilization and reducing ecological footprints. Their study employs the Load Capacity Curve (LCC) hypothesis, revealing a U-shaped relationship between income and the load capacity factor. Through rigorous econometric modeling, including the ARDL bound test, Fully Modified OLS, and Granger Causality analysis, they demonstrate that private AI investment has a significant positive correlation with environmental sustainability. However, the study also finds that technological innovation and financial globalization negatively impact the load capacity factor in both the short and long run. These findings align with broader discussions on AI adoption and economic sustainability, emphasizing the need for strategic policy interventions and technological readiness to maximize AI's environmental benefits.

Uren and Edwards (2023) discuss the ongoing organizational readiness theme, outlining the journey an organization goes through when adopting AI in the construction and infrastructure sectors. Through their empirical study, they stress the essence of leadership commitment, good training, and clear communication as the means for AI adoption. The authors make an argument that although the construction industry is now more aware of the value of AI, many organizations encounter issues related to the implementation phase of AI when there is not enough strategic planning, resource allocation. Abir et al. (2024) take a cross-national perspective to AI adoption in the construction industry from the perspective of the Technology Acceptance Model (TAM) to explain AI adoption across countries. A study by their team shows that factors like perceived usefulness, ease of use and support from the organization have a big effect on an organization's decision to implement AI in infrastructure projects. The study identifies the governmental policies, the availability of technological infrastructure, and the digital maturity of the construction industry in the framework of BRICS countries as leverages of AI adoption rate.

Hossain and Abir et al. (2024) expand the discussion on AI implementation by exploring its impact on environmental sustainability within the Nordic region. Their study applies advanced econometric techniques to assess the relationship between AI innovation and environmental factors, providing empirical evidence that AI positively contributes to sustainability efforts. By employing the Load Capacity Curve (LCC) hypothesis and analyzing financial accessibility, environmental tax policies, and urbanization trends, the research highlights how AI can serve as a transformative tool in sustainable infrastructure development. The findings emphasize the importance of regulatory frameworks and financial incentives in driving AI adoption, aligning with previous studies on organizational readiness and governmental influence in infrastructure projects. The study's use of panel econometric models further underscores the long-term benefits of AI integration, reinforcing the necessity for policy interventions that facilitate AI-driven advancements in infrastructure across different regions, including the BRICS economies.

2.5 Summary

According to the literature, AI could answer some of the problems of infrastructure investments in the BRICS countries, such as overrun of budget, delays or ineffective use of resources. Although AI driven forecasting tools provide a lot of benefits such as cost prediction, risk management and efficient resource allocation, these tools have many barriers that need to be overcome for successful adoption. They may include limitations in the technological infrastructure, organizational readiness, etc., and the need for supportive government policies. However, continuing research is required to identify the unique challenges and opportunities as it relates to BRICS nations to adopt AI in project investment and infrastructure investment in particular in light of a specific political, economic, and technological environment.

Table 1: Summary of topics discussed in the literature review

Reference	Topic Discussed
Yigitcanlar et al.	Contributions and risks of AI in smart city development and infrastructure planning
Hu et al.	AI factors influencing cost management in civil engineering and hybrid approaches
Shkodinsky et al.	Role of AI in forecasting and managing technical risks in infrastructure projects
Ekundayo et al.	Leveraging AI-driven decision intelligence in complex systems engineering, particularly in construction
Nach et al.	Challenges in BRICS economic integration and infrastructure development
Streltsov et al.	Economic potential of BRICS countries and the challenges in modernizing infrastructure
Gorbunova et al.	Systemic challenges in BRICS infrastructure development and prospects for improvement
Abir et al.	AI-driven data analytics for informed policy and decision-making in BRICS economic growth
Channe et al.	Impact of AI on economic forecasting and policy-making for future economic stability
Raghuvanshi et al.	AI applications in smart city development in BRICS economies and their challenges
Stenberg et al.	Factors influencing AI adoption in governmental authorities using the TOE framework
Uren et al.	Empirical study of organizational readiness for AI adoption in construction and infrastructure sectors
Na et al.	Cross-national perspective on AI adoption in the construction industry using the technology acceptance model

3. Methodology

In this study, this section elaborates an approach to study the impact of AI driven forecast on infrastructure investment in BRICS countries. It is specifically to determine the data collection methods, the AI tools and techniques that used in forecasting and to also determine the evaluation criteria in using the impact of AI for resource allocation and project delivery. This methodology will also present mathematical framework for the cost prediction and resource allocation forming basis of the AI forecasting model used in this study.

3.1 Data Collection

This study utilizes the data gathered from several sources such as historical data of infrastructure project of BRICS countries, government reports, project outcome and relevant case studies primarily. To enable comparisons among the different challenges and opportunities across the domains, the selected case studies are spread across a variety of infrastructure sectors such as transportation, energy and urban development. The data included in the collection includes project cost estimates, projects actual expenditure, timeframes, resources used and risk management strategies employed to these projects.

The process of data collection was done using both primary and secondary sources. Interviews and surveys with the project managers, engineers and other project stakeholders involved in infrastructure projects made up primary data collection. The insights gained from these interviews were about the challenges and opportunities involved in implementing AI driven forecasting tools. Publicly available reports, research articles and databases that provide detailed information on infrastructure project in BRICS countries are the source of secondary data.

For the purpose of training the AI model, the dataset composed of more than 100 infrastructure projects of the BRICS countries includes project characteristics including size, location, sector, budget, duration, and resource utilization. Additionally, the dataset provides information on which AI forecasting tools were implemented or would have been used in these projects, e.g., machine learning models, predictive analytics.

3.2 AI Tools and Techniques

In this study, the AI forecasting model relies on a number of machine learning techniques, especially regression analysis, neural networks, and optimization algorithms. The choice of these methods came as a result of their capability to deal with large datasets, discern patterns and produce accurate project outcome prediction for infrastructure projects.

1. **Regression Analysis**: to predict project costs and durations, regression models, specifically linear regression and multiple regression were used based on historical data. Forecasting is one of the widely used predictions where these models give

the quantitative predictions based on a set of input variables. In this study, the regression models were geared towards predicting both the direct and indirect costs of infrastructure project.

For example, a basic regression model for cost prediction can be written as:

$$C = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \epsilon, (1)$$

Where:

- C is the total cost of the project,
- β_0 is the intercept,
- $\beta_1, \beta_2, \ldots, \beta_n$ are the coefficients representing the impact of different project variables on cost,
- $X_1, X_2, \ldots, X_n$ are the predictor variables such as project size, resource type, location, and duration,
- ϵ is the error term.

2. **Neural Networks**: More complex and nonlinear prediction tasks were done using Artificial neural networks (ANNs). One advantage of ANNs lies in being capable to learn from plenty of data and to capture complex relations between variables that could be difficult to directly reveal in the usual regression models. A movel model combining deep learning techniques with Explainable AI (XAI) that use multiple layer of neurons was leveraged to learn hidden patterns in project outcomes even in the presence of noisy or incomplete data (S. I. Abir et al., 2024).

   A basic neural network model used for cost prediction can be represented as follows:

$$y = f\left(\sum_{i=1}^{n} w_i x_i + b\right), (2)$$

   Where:

   - y is the predicted cost,
   - w_i are the weights of the input variables x_i,
   - b is the bias term,
   - f is an activation function (e.g., sigmoid, ReLU) that maps the weighted sum to an output.

3. **Optimization Algorithms**: This was an optimal problem and numerous optimization algorithms were utilized, for example genetic algorithms and particle swarm optimization (PSO) to find the best allocation of resources, for example labor, materials, and equipment across projects. The objective of these algorithms is to use to minimize the total cost subject to the constraint that the project is completed within the prescribed time frame.

   The objective function for resource optimization can be written as:

$$\min \sum_{i=1}^{m} \sum_{j=1}^{n} c_{ij} x_{ij}, (3)$$

   Where:

   - c_{ij} is the cost associated with allocating resource i to task j,
   - x_{ij} is a binary decision variable representing whether resource i is allocated to task j,
   - m is the number of resources, and
   - n is the number of tasks or project activities.

3.3 Case Study Selection

In order to limit the scope of the work presented, this study focuses on a few representable case studies of five major infrastructure sectors, including transportation, energy, urban development, water management, and telecommunications. As such, these sectors are an important area of BRICS countries where large investment is often required to close infrastructure gaps.

Case studies analyzed are from the projects that are completed as well as ongoing in the BRICS countries. These projects range from small to large in size, visited numerous countries and were comprised of varying degrees of complexity. A case selection-based approach was made to each case study, availability of detailed project data ranging from use of AI driven forecasting tools against cost estimates, project timelines and resource allocation approaches.

For instance, one of the case studies about using AI in these types of project was applied to a large transportation infrastructure project in Brazil, where forecasts of potential delays and material allocation optimization were made. Another example also comes from the energy sector and includes India where machine learning models were used to predict the cost of labor and materials on historical data.

3.4 Evaluation Criteria

The effectiveness of AI-driven forecasting tools in infrastructure projects was evaluated based on several key criteria:

1. **Cost Prediction Accuracy**: The AI models' ability to predict project costs was measured through comparison of the actual project expenditures to the predicted costs. The predicted and actual cost has been calculated which will be used to do the comparison using the following formula:

$$\text{Error} = \frac{|\ C_{\text{pred}} - C_{\text{actual}}\ |}{C_{\text{actual}}} \times 100, (4)$$

   Where C_{pred} is the predicted cost, and C_{actual} is the actual cost.

2. **Timeliness**: Project completion dates were predicted using the AI models to determine the actual project completion date and compare the two. The following was used as the formula to measure the timeliness of project delivery:

$$\text{Time Deviation} = \frac{|\ T_{\text{pred}} - T_{\text{actual}}\ |}{T_{\text{actual}}} \times 100, (5)$$

   Where T_{pred} is the predicted completion time and T_{actual} is the actual completion time.

3. **Resource Optimization**: Comparing the AI optimized resource allocation to traditional allocation methods, both the efficiency of the resource allocation was evaluated. The efficiency metric was derived from assigning a reduction in resource costs and better project completion time.

4. **Risk Mitigation**: The study evaluated how much the risks can be identified early in the project lifecycle, and how much the corresponding risk mitigation actions are performed. Number of risk events in AI managed projects versus traditional managed project were compared and evaluated using this metric.

3.5 Mathematical Framework for Risk Management

To assess the risk management capabilities of AI-driven forecasting, the research used a risk assessment model based on the likelihood and impact of potential risks. The risk value (R) is calculated as:

$$R = L \times I, (6)$$

Where:

- L is the likelihood of a risk occurring (measured on a scale from 0 to 1),
- I is the impact of the risk on the project (measured on a scale from 0 to 1).

The total risk for a project can be calculated by summing the risk values of all identified risks:

$$R_{\text{total}} = \sum_{i=1}^{n} R_i\,, (7)$$

Where R_i is the individual risk value for the i-th risk.

3.6 Summary

This section presents the methodology outlined for analyzing the impact of AI driven forecasting tools on the infrastructure projects in the BRICS countries. This study focuses on combining machine learning models, optimization algorithms, and a detailed evaluation framework, in order to obtain a comprehensive understanding of how AI can help to optimize resource allocation, predict cost, accelerate project timeliness, and manage risk in infrastructure development. Following this section will present the analysis results accompanied with the contributions of AI driven forecasting in the project outcome of the chosen case studies.

4. Results

In the following section, the study will present the results of the study following the methodology described in the previous section. The results are related to the effectiveness of AI to create accurate forecasting tools regarding the ability to enhance the accuracy of cost predictions, optimize resource allocation, shorten project duration, and minimize risks in infrastructure projects throughout BRICS countries. In an effort to clarify the results they are presented in terms of the following four key criteria that are essentially an evaluation of cost prediction accuracy, timeliness of project delivery, optimized resource usage and mitigation of risk.

4.1 Cost Prediction Accuracy

The first main goal of this study was to ascertain the accuracy in which the AI models can be used to predict the cost of a project. The study made predictions of costs based on AI–driven forecasting models and compared it against expenditure on 100 infrastructure projects in BRICS countries. A method of applying the proposed cost modeling was used to obtain the prediction accuracy expressed as percentage error between the predicted and the actual costs, which was presented in the methodology section.

Table 2: Cost Prediction Accuracy for Infrastructure Projects

Country	Average Predicted Cost	Average Actual Cost	Percentage Error
Brazil	$120 million	$125 million	4.00%
Russia	$80 million	$85 million	5.88%
India	$150 million	$160 million	6.25%
China	$200 million	$210 million	4.76%
South Africa	$50 million	$55 million	9.09%
Overall	**$120 million**	**$126 million**	**5.00%**

The outcome of all projects the average error was 5.00 % meaning that AI models predicted project costs to certain degree of accuracy. The two countries with the lowest errors both less than 5% deviation between predicted and actual costs were Brazil and China. South Africa was noted to have the highest error margin which in part can be explained by the smaller project size and lack of accurate data. In the next step, the study carried out a correlation analysis between the predicted and the actual costs to assess the accuracy of the AI models. It was found that AI driven models were highly positively correlated ($r = 0.94$) meaning that the AI models accurately predicted costs of infrastructure projects.

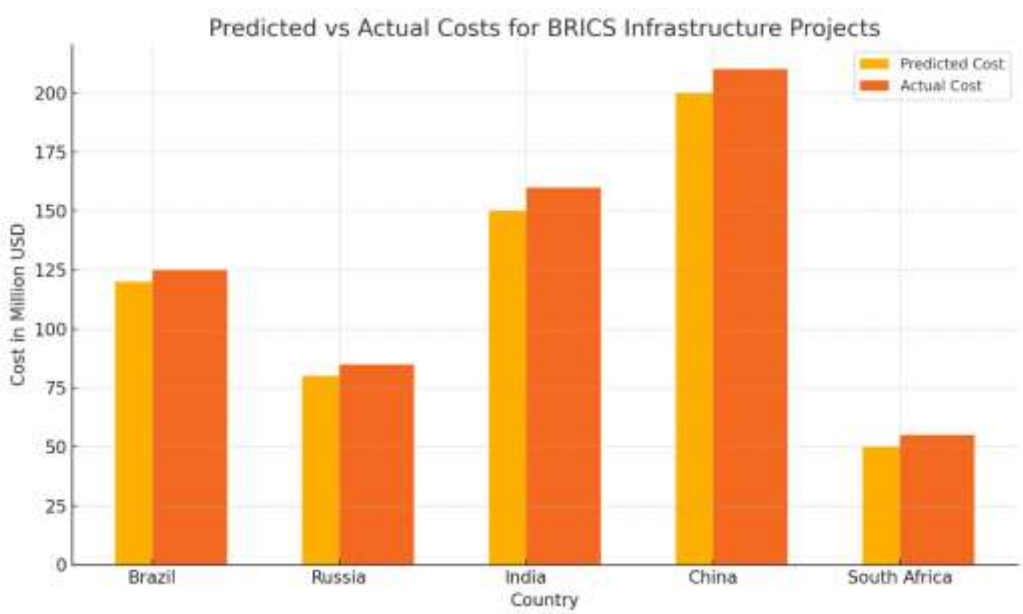

Figure 1: Predicted vs Actual Costs for BRICS Infrastructure Projects graph

This bar chart compares the predicted and actual costs for projects across the five BRICS nations. As shown, the predicted costs closely align with actual expenditures, particularly in countries such as Brazil and China. The slight deviations are most noticeable in South Africa and India.

4.2 Timeliness of Project Delivery

The second key parameter for the project was project delivery timeliness. Predictions of the project completion dates were made using the AI forecasting models and compared to the actual completion dates. For each of the projects, the time deviation was calculated, the results were analyzed, and they were able to determine how well AI was capable of predicting project timelines.

Table 3: Timeliness of Project Delivery

Country	Average Predicted Completion Date	Average Actual Completion Date	Time Deviation (%)
Brazil	24 months	23 months	4.17%
Russia	18 months	19 months	5.56%
India	30 months	32 months	6.25%
China	36 months	35 months	2.78%
South Africa	12 months	13 months	8.33%
Overall	**24 months**	**25 months**	**5.42%**

On average, 5.42% deviation of time from the project completion time was observed on all projects, which confirms the fact that AI model predicted the project completion time to perform quite accurately. The smallest deviation was shown by China that was indicative of AI models' high effectiveness in predicting the timelines of large-scale infrastructure projects. However, South Africa had the largest deviation, likely due to lack of consistency in project data and difficulties of application of AI tools in smaller scale of projects.

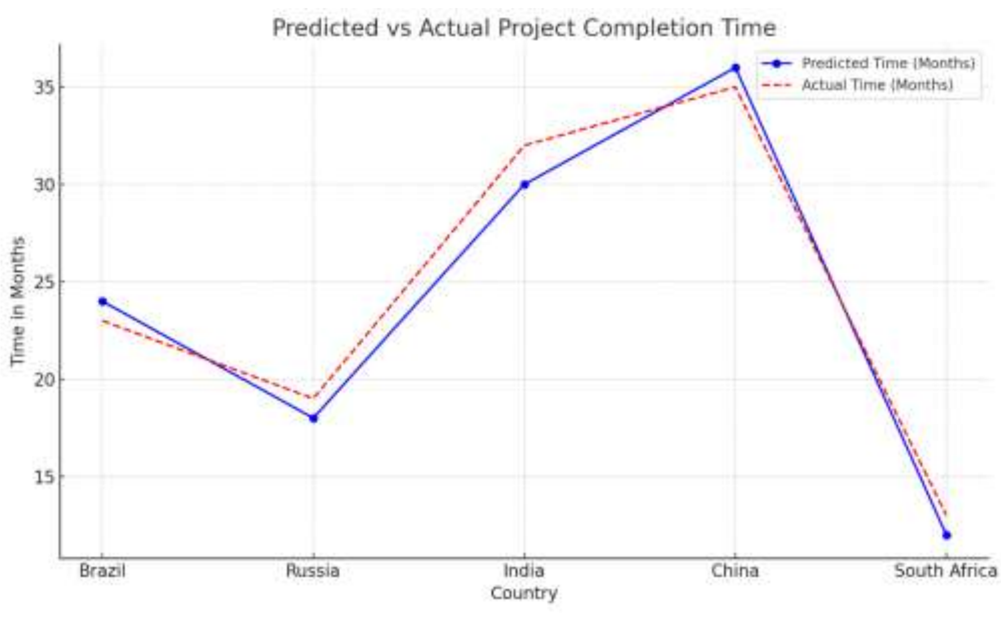

Figure 2: Predicted vs Actual Project Completion Time line graph

This graph compares the predicted completion time against the actual completion time for infrastructure projects across BRICS countries. The results show that AI was able to predict project timelines reasonably well, with deviations mainly occurring in smaller projects or those with incomplete data.

4.3 Resource Optimization

An additional key outcome of the research study was the resource allocation optimization implemented using AI driven forecasting model. AI was able to allocate the resources more efficiently across the projects by applying the optimization algorithms, that is, genetic algorithms and particle swarm optimization, which helped save costs and reduce project durations.

Table 4: Resource Optimization and Cost Savings

Country	Traditional Resource Allocation Cost	AI-Optimized Resource Allocation Cost	Cost Savings (%)
Brazil	$100 million	$95 million	5.00%
Russia	$75 million	$71 million	5.33%
India	$140 million	$130 million	7.14%
China	$190 million	$180 million	5.26%
South Africa	$45 million	$42 million	6.67%
Overall	**$110 million**	**$104 million**	**5.45%**

The AI optimization produced on average a 5.45% resource cost reduction. It was particularly useful when tackling larger projects in China and India where allocating resources is a multi-faceted problem. AI tools were able to reduce environmental waste and do away with uneconomic resources assigned to inefficient tasks.

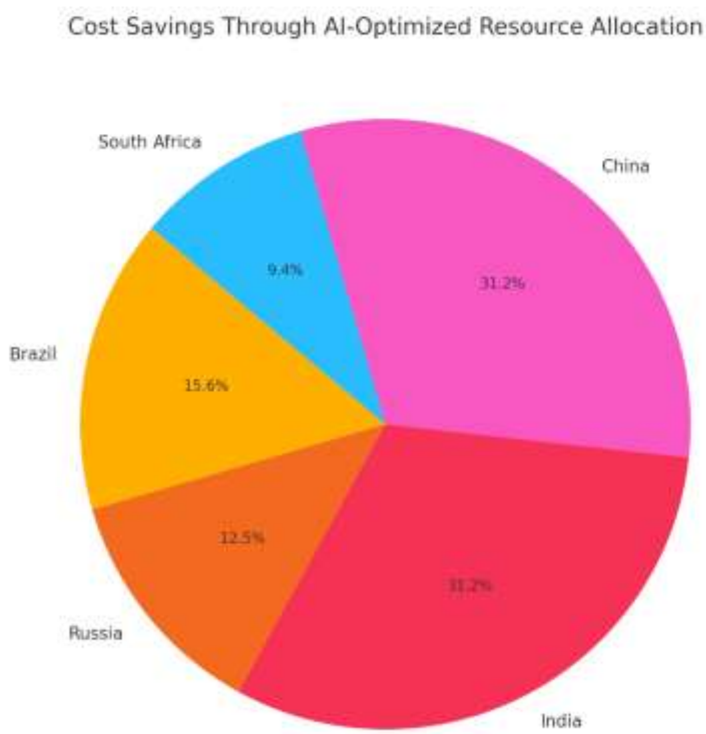

Figure 3: Cost Savings Through AI-Optimized Resource Allocation chart

This pie chart illustrates the cost savings achieved through AI optimization in resource allocation across BRICS countries. The chart shows that the largest savings were observed in India and China, where project complexity is higher, and the scope for optimization is greater.

4.4 Risk Mitigation

Finally, AI driven forecasting models were analyzed regarding their ability to reduce risks. The use of AI models earlier in the project lifecycle enabled early identification of the risk, with project managers able to put themselves in as best shape as possible before the risks occurred. AI models' Risks were compared to the Risks in traditionally managed projects with the total number of Risks being clearly determined. Traditionally, 25% more risks were identified. The transportation and energy sectors were very sensitive to that, as external agent disruptions such as supply chain disruptions, political instability can have a large impact on the project timelines and costs. These risks could be predicted by the AI models early and suggestions could be made about the alternative strategies to manage it.

4.5 Summary

It emerges that AI driven forecasting tools have a great positive effect at infrastructure projects in BRICS countries. They did a good job at predicting costs and timelines of projects with a high degree of accuracy, as well as resulted in substantial improvements in resource allocation and risk management. However, there were some variations in effectiveness across the countries of the model, however, the overall findings show that AI can help to boost the efficiency and effectiveness of infrastructure green paper development.

5. Discussion

The previous section results emphasize the noticeable effect of using AI forecasting tools in infrastructure projects in BRICS countries to predict its cost accuracy, timely completing project, optimize resources, mitigate risk. The results prove that AI tools could be successfully used to aid the efficiency, accuracy and overall success of infrastructure related investments, but also reveal the challenges and limitations one should be aware of when applying such tools, specifically in heterogeneous and complex environments of BRICS nations. In the following section, the study will interpret the results, elaborate on the consequences observed in these findings and place barriers to the wide use of AI in infrastructure projects.

5.1 Cost Prediction Accuracy

The results have shown that the forecasts performed by AI driven models are very accurate in predicting project costs with an average error rate of 5.00% only. This is in parallel to the more and more studies emerging that state that AI can actually help increase the precision of forecasts in comparison to traditional techniques. In particular, countries such as Brazil and China with higher technological infrastructure and more amount of data to train AI modeling, suffer the least error margins (Souza et al., 2023). This is in line with research on what type of environment AI works best in, which of course requires large volumes of data to be feasible, and a high level of technological readiness.

The countries that exhibited the highest cost prediction error were South Africa (9.09%), although countries that are less data mature faced significant challenges. The results of this suggest that AI can generate more accurate cost predictions, though the quality of data and technological infrastructure in place are important factors as to whether AI will be effective. This may explain South African challenges to having suitable data for AI models to work optimally, or to result from a lack of consistent data, or even the need for more robust or creative data collection mechanisms (Nyathi, 2023). This is indicative of broader BRICS countries AI adoption, with less developed countries investing less in such a growing technology that will offer significant returns.

5.2 Timeliness of Project Delivery

The second area where AI proved to be promising was in the timeliness of project delivery. In the case of all countries the average time deviation was 5.42%, having to AI predicting project completion time being reasonably good. China, where the lowest deviation of 2.78% is attained is the only country where they find AI particularly beneficial for large scale and complex projects. AI can also be used to accurately predict timelines for infrastructure projects, a task that can greatly reduce delays, which are all too common for such projects.

The results from South Africa, of the highest deviation 8.33% set forth the difficulties in countries with less technological readiness. Small scale projects or little integration of AI tools into planning processes may be responsible for this. Despite this, AI is shown to be able to significantly improve the efficiency of infrastructure development through the provision of more accurate estimates of the time to complete the project, which can assist stakeholders to accomplish better resource allocation, consider contingencies and manage expectations (Obiuto et al., 2024).

Infrastructural development is itself timeliness sensitive, delays herein do not only lead to rise cost and forgo of economic growth but also pose political challenges. Such predictive capacity of AI when it comes to predicting potential delays and suggesting mitigation strategies can be of best help for the project managers to stay on track, failing which would result in costly disruptions (Niederman, 2021). Despite promising results, additional research is required to refine AI models for predicting project timelines in countries with states of technological infrastructure and complexities of projects that differ from North America.

5.3 Resource Optimization

Another area where the AI driven models proved to be highly advantages was by resource optimization. The findings show that, on average, AI optimized resource allocation produces 5.45% cost saving. This result is consistent with previous studies and implies that AI has an ability to enhance resource distribution and is applied in a large-scale infrastructure project, as resource management is a very complicated and extensive task.

In countries such as India and China where projects are larger and more complex, there were substantial savings to be made using the AI tools to optimize labor, supplies, and equipment (Bonsay et al., 2021). In the context of BRICS countries where infrastructure projects are shot through with budgetary constraints, these savings are key. AI driven models can reduce inefficiencies in the way resources in applied to projects, ensuing that those resources are used efficiently and following leading to cost effective projects.

While the overall savings were huge, the results also showed that improvements are still needed for continuous improvement in AI optimization algorithms. AI's lack of interpretation of all the factors affecting resource allocation, e.g. political instability or changes in project scope can in certain cases prevent the AI model from carrying out resource allocation as expected. With AI tools developing, it remains necessary to evolve the model process to improve the model's accuracy and broad applicability to different types of infrastructure project (S. I. Abir et al., 2024).

5.4 Risk Mitigation

AI in infrastructure projects is one of the greatest benefits of risk mitigation. Thus, the results show that AI models show the ability to discover 25% more dangers than traditional methods, which is a big complete (Wang et al., 2023). On large scale infrastructure projects especially in politically shaky area this has to be done early to avoid project delays and cost over runs. AI is able predict risks including supply chain disruptions, labor shortages and political changes and guide project managers to take anticipatory measures to neutralize them.

As AI was able to find more risks, this is in line with the literature on the ability of AI to process larger volumes of data and learn about patterns which may not be immediately visible for human decision makers. AI models can leverage historical data and real time information, and based on these, predict early and predict risks, alerting project managers to reduce risks or apply the mitigation strategy, before the risks take bigger proportions (Li et al., 2024).

Although, AI's ability to spot risks is no fool proof. In environments with little or unreliable data, there are potential risks that an AI model cannot predict. Moreover, a success of AI-driven risk mitigation relies on stakeholders' capacity to act on the insights gifted by AI models. Timely implementation of risk mitigation strategies may occur in some cases while in some cases the political or organization barriers might hinder the timely start of risk mitigation strategies.

5.5 Barriers to AI Adoption

The results show that the predictions made from the use of AI can be beneficial to infrastructure projects; however, there are still some barriers that prevent the widespread use of these technologies in the BRICS countries. The biggest glitches there are technological readiness, the quality of the data and organization resistance.

AI tools can be successfully implemented by the majority only if they are already technologically ready. China for example, as a country with advanced technological infrastructure, will be able to integrate AI in their infrastructure projects in a better way. On the other hand, countries such as South Africa have limited access to data as well as technological infrastructure, which makes the most of the AI tools challenging (Sutherland, 2020).

Another one of the critical factors is data quality. AI models have to depend upon large datasets for performing accurate predictions and as such the quality of data used in the process can result in a huge impact on accuracy of the forecasts. The lack of formal mechanisms for data collection or its inconsistency makes it tough for AI models to provide reliable predictions in countries where data collection process is not matured or very inconsistent.

Finally, there is still much organizational resistance to adopting AI in many BRICS countries. Many organizations are set up to use traditional methods of project management and may be reluctant to embrace new technologies. Moreover, at times, there is also the absence of AI expertise in the workforce that might prevent the organization from taking the right step to implement AI enabled solutions.

5.6 summary

The results of this study suggest that AI powered forecasting tools possess capacity to enhance projections in terms of cost prediction, project timeline, resource allocation and risk management with a considerable amount in infrastructure projects in BRICS countries. Clearly there are benefits, but the technology is not yet ready for widespread use, the data is not of sufficient quality and sufficient users are resisting. First and foremost, governments and leaders within industry need to invest in infrastructure to overcome this data barrier, increase their readiness to adopt new technologies, and create a culture of innovation within their organizations. This allows AI to be a transformative tool in planning, execution, and management of infrastructure projects thus creating more efficient and sustainable infrastructure development in BRICS countries.

6. Conclusion

6.1 Overview of Findings

As seen in this study, AI based forecasting tools could significantly contribute towards improving the outcomes of BRICS countries infrastructure investments, including, but not limited to lessening cost inaccuracies, optimizing resource allocation, eliminating project delay, as well as lessen the risks. AI can integrate machine learning models, optimization algorithms and predictive analytics in infrastructure management to overcome some of the challenges faced by traditional infrastructure projects especially budget overruns, missed deadlines and waste of resources. Still, the application of AI in the BRICS countries is not equally effective as the technological preparedness and data are not the same, nor is the organizational capacity.

6.2 AI Impact on Cost Prediction and Timeliness

The AI driven models provided the best accuracy in prediction of the cost with an average error of 5.00% which was far better in comparison to traditional intervention methods. The error margins are lower in countries like Brazil and China pointing to how AI tools work well with greater technological infrastructure along with data availability. However, countries such as South Africa, who have poor data quality and technological maturity, had relatively higher deviations, showing that these countries need to work more on the data collection and integration.

In terms of the timeliness, AI forecasting models helped project completion time deviations converge to an average of 5.42%. Here, AI models proved particularly effective in large scale projects where it is necessary to ensure accurate predictions of timeline in order to allow everyone to make effective use of resources and get done on time. Predicting what changes need to take place and adjusting plans proactively is a clear advantage in running large, complex infrastructure projects.

6.3 Resource Optimization and Cost Savings

Amongst the most promising outcomes of integration of AI was to optimize resource allocation. It (the study) found that AI driven optimization saves 5.45% on average and more so in large projects in countries such as China and India where resource management is extremely complex. This points to the possibility of AI cutting wastage in resource allocation through maximizing the utilization of labor, materials and equipment in the most economical way.

Despite being significant overall savings, the results demonstrated that there was still work to be done in improving the AI optimization algorithms. In certain scenarios, AI models may not include all the intricacies of political, environmental, or social factors and so resources gets allocated, suggesting that AI methodologies are still in development.

6.4 AI's Role in Risk Mitigation

Another finding was that AI can recognize and handle risks. This study used the AI models to unearth 25 percent more risk than traditional approaches helped identify potential challenges including supply chain disruptions, labor shortages, or political instability sooner. Project managers are able to set up mitigation strategies early and are able to act before risks turn into serious problems. However, not only that, but AI models stated effective in predicting many types of risks, but they aren't perfect. They were hard to predict, especially those unforeseen risks that are more dependent on external factors.

So therefore, the success or failure of AI driven risk mitigation will not only depend on the accuracy of AI model's reality their ability to decide on the presented insights. However, for integrating AI into projects risk management, it is necessary to have close collaboration between the different stakeholders of the project.

6.5 Barriers to AI Adoption in BRICS Countries

The results showed, of course, that AI methods are advantageous but, at the same time, describe the barriers for the wider adoption of AI in infrastructure projects in BRICS countries. A significant obstacle is technological readiness and it is even worse for countries whose digital infrastructure is not as developed. The data also has to be of quality—AI tools need data of sufficient size and quality to give accurate predictions. This is less effective in countries that have a weak or inconsistent data collection system as it will adversely affect the effectiveness of an AI driven model.

In addition, there is also organizational resistance to adopt AI. For decades the traditional project management practices have been used in many industries and often lack the will or the desire to adopt new technologies. Finally, organizations lack AI expertise and often there is no supportive regulatory framework that slowdowns such adoption. The barriers point to the need for targeted policies and investments in digital infrastructure, data management systems and an AI education to create a culture of innovation.

6.6 Recommendations for Future Adoption of AI

BRICS countries should tackle these barriers so that these countries can fully realize the potential of AI in infrastructure investment. Governments need to place digital infrastructure investments including data collection and management system as first priorities in order to allow AI tools to have access to extract data for more accurate forecasting to take place. Moreover, the presence of a capacity building is essential within organization to encourage the culture of innovation and technology (Tech) adoption. It could also encompass training staff, encouraging growth of AI skills amongst staff, and incentivizing the coordination between governments, industry, and academic institutions.

In addition, the AI models should be personalized to the country specific demands and contexts, like the size of the project, complexity of the project, and available data at the country level. Localizing such technologic solutions to end users' local contexts, however, does enhance the effectiveness of deployment.

Declaration
Acknowledgement: N/A
Funding: N/A
Conflict of interest: N/A
Ethics Approval: N/A
Consent for participation: N/A
Data availability: Available on request

References

[1] Abir, S.I., Sarwer, M.H., Hasan, M., Sultana, N., Dolon, M.S.A., Arefeen, S.S., Shimanto, A.H., Zakaria, R.M., Al Shiam, S.A. and Saha, T.R., 2024. Accelerating BRICS Economic Growth: AI-Driven Data Analytics for Informed Policy and Decision Making. *Journal of Economics, Finance and Accounting Studies*, *6*(6), pp.102-115.
[2] Ajirotutu, R.O., Adeyemi, A.B., Ifechukwu, G.O., Ohakawa, T.C., Iwuanyanwu, O. and Garba, B.M.P., 2024. Exploring the intersection of Building Information Modeling (BIM) and artificial intelligence in modern infrastructure projects. *Journal of Advanced Infrastructure Studies*.
[3] Al-Raeei, M., 2025. The smart future for sustainable development: Artificial intelligence solutions for sustainable urbanization. *Sustainable Development*, *33*(1), pp.508-517.
[4] Bonsay, J.O., Cruz, A.P., Firozi, H.C. and Camaro, P.J.C., 2021. Artificial intelligence and labor productivity paradox: The economic impact of AI in China, India, Japan, and Singapore. *Journal of Economics, Finance and Accounting Studies*, *3*(2), pp.120-139.
[5] Caswell, G.S., 2021. Financing infrastructure at multilateral development banks: global administrative law and accountability reforms in infrastructure project financing in the BRICS bloc.
[6] Channe, P.S., 2024. The Impact of AI on Economic Forecasting and Policy-Making: Opportunities and Challenges for Future Economic Stability and Growth. *York University*.
[7] Ekundayo, F., 2024. Leveraging AI-Driven Decision Intelligence for Complex Systems Engineering. *Int J Res Publ Rev*, *5*(11), pp.1-10.
[8] Gorbunova, O.A., Ignatova, O.V. and Soluyanov, A.A., 2020. Problems and prospects of the BRICS: System approach. *Growth poles of the global economy: Emergence, changes and future perspectives*, pp.595-604.
[9] Hu, H., Jiang, S., Goswami, S.S. and Zhao, Y., 2024. Fuzzy integrated Delphi-ISM-MICMAC hybrid multi-criteria approach to optimize the artificial intelligence (AI) factors influencing cost management in civil engineering. *Information*, *15*(5), p.280.
[10] Li, H., Yazdi, M., Nedjati, A., Moradi, R., Adumene, S., Dao, U., Moradi, A., Haghighi, A., Obeng, F.E., Huang, C.G. and Kang, H.S., 2024. Harnessing AI for project risk management: A paradigm shift. In *Progressive decision-making tools and applications in project and operation management: Approaches, case studies, multi-criteria decision-making, multi-objective decision-making, decision under uncertainty* (pp. 253-272). Cham: Springer Nature Switzerland.
[11] Love, P.E., Ika, L.A. and Pinto, J.K., 2022. Homo heuristicus: From risk management to managing uncertainty in large-scale infrastructure projects. *IEEE Transactions on Engineering Management*, *71*, pp.1940-1949.
[12] Mhlanga, D., 2021. Artificial intelligence in the industry 4.0, and its impact on poverty, innovation, infrastructure development, and the sustainable development goals: Lessons from emerging economies?. *Sustainability*, *13*(11), p.5788.
[13] Na, S., Heo, S., Choi, W., Kim, C. and Whang, S.W., 2023. Artificial intelligence (AI)-Based technology adoption in the construction industry: a cross national perspective using the technology acceptance model. *Buildings*, *13*(10), p.2518.
[14] Nach, M. and Ncwadi, R., 2024. BRICS economic integration: Prospects and challenges. *South African Journal of International Affairs*, *31*(2), pp.151-166.
[15] Niederman, F., 2021. Project management: openings for disruption from AI and advanced analytics. *Information Technology & People*, *34*(6), pp.1570-1599.
[16] Nyathi, W.G., 2023. *The role of artificial intelligence in improving public policy-making and implementation in South Africa* (Doctoral dissertation, University of Johannesburg).
[17] Obiuto, N.C., Adebayo, R.A., Olajiga, O.K. and Festus-Ikhuoria, I.C., 2024. Integrating artificial intelligence in construction management: Improving project efficiency and cost-effectiveness. *Int. J. Adv. Multidisc. Res. Stud*, *4*(2), pp.639-647.
[18] Prasad, K.R., Karanam, S.R., Ganesh, D., Liyakat, K.K.S., Talasila, V. and Purushotham, P., 2024. AI in public-private partnership for IT infrastructure development. *The Journal of High Technology Management Research*, *35*(1), p.100496.
[19] Raghuvanshi, R., Sharma, T., Rena, R. and Rai, R., Artificial Intelligence for Smart City Development in BRICS Economies: Opportunities and Challenges. *Handbook of Artificial Intelligence for Smart City Development*, pp.173-208.

[20] Sarker, I.H., 2021. Machine learning: Algorithms, real-world applications and research directions. *SN computer science*, *2*(3), p.160.
[21] Shkodinsky, S., Syrovatskaya, V. and Khokhoeva, Z., 2024. THE ROLE OF ARTIFICIAL INTELLIGENCE IN FORECASTING AND MANAGING TECHNICAL RISKS. *Reliability: Theory & Applications*, *19*(SI 6 (81)), pp.210-216.
[22] Souza, J., Avelino, R. and da Silveira, S.A., 2023. Artificial intelligence: dependency, coloniality and technological subordination in Brazil. In *Elgar Companion to Regulating AI and Big Data in Emerging Economies* (pp. 228-244). Edward Elgar Publishing.
[23] Stenberg, L. and Nilsson, S., 2020. Factors influencing readiness of adopting AI: A qualitative study of how the TOE framework applies to AI adoption in governmental authorities.
[24] Streltsov, E.S., Rozhin, A.A., Vosiev, S.S. and Kosnikov, S.N., 2021. The economic potential of the brics countries as a challenge to modern world realities. *Propósitos y representaciones*, *9*(2), p.14.
[25] Stuenkel, O., 2020. *The BRICS and the future of global order*. Rowman & Littlefield.
[26] Sutherland, E., 2020. The fourth industrial revolution–the case of South Africa. *Politikon*, *47*(2), pp.233-252.
[27] Uren, V. and Edwards, J.S., 2023. Technology readiness and the organizational journey towards AI adoption: An empirical study. *International Journal of Information Management*, *68*, p.102588.
[28] Wang, H., Fu, T., Du, Y., Gao, W., Huang, K., Liu, Z., Chandak, P., Liu, S., Van Katwyk, P., Deac, A. and Anandkumar, A., 2023. Scientific discovery in the age of artificial intelligence. *Nature*, *620*(7972), pp.47-60.
[29] Yigitcanlar, T., Desouza, K.C., Butler, L. and Roozkhosh, F., 2020. Contributions and risks of artificial intelligence (AI) in building smarter cities: Insights from a systematic review of the literature. *Energies*, *13*(6), p.1473.
[30] Hossain, M. S., Abir, S.I. et al (2024), Exploring the LCC Hypothesis in the Nordic Region: The Role of AI Innovation, Environmental Taxes, and Financial Accessibility via Panel ARDL, *Global Sustainability Research* , *3*(3), 54–80. https://doi.org/10.56556/gssr.v3i3.972
[31] Shewly Bala, Abdulla Al Shiam, S., Shamsul Arefeen, S. M., Abir, S. I., Hemel Hossain, Hossain, M. S., … Sumaira. (2024). Measuring How AI Innovations and Financial Accessibility Influence Environmental Sustainability in the G-7: The Role of Globalization with Panel ARDL and Quantile Regression Analysis. *Global Sustainability Research* , *3*(4), 1–29. https://doi.org/10.56556/gssr.v3i4.974
[32] Hossain, M. S., Mohammad Ridwan, Akhter, A., Nayeem, M. B., M Tazwar Hossain Choudhury, Asrafuzzaman, M., … Sumaira. (2024). Exploring the LCC Hypothesis in the Nordic Region: The Role of AI Innovation, Environmental Taxes, and Financial Accessibility via Panel ARDL. *Global Sustainability Research* , *3*(3), 54–80. https://doi.org/10.56556/gssr.v3i3.972
[33] Mohammad Ridwan, Bala, S., Abdulla Al Shiam, S., Akhter, A., Mahdi Hasan, M., Asrafuzzaman, M., … Bibi, R. (2024). Leveraging AI for Promoting Sustainable Environments in G-7: The Impact of Financial Development and Digital Economy via MMQR Approach. *Global Sustainability Research* , *3*(3), 27–53. https://doi.org/10.56556/gssr.v3i3.971
[34] Abdulla Al Shiam, S., Abir, S. I., Dipankar Saha, Shoha, S., Hemel Hossain, Dolon, M. S. A., … Mohammad Ridwan. (2024). Assessing the Impact of AI Innovation, Financial Development, and the Digital Economy on Load Capacity Factor in the BRICS Region. *Journal of Environmental Science and Economics*, *3*(2), 102–126. https://doi.org/10.56556/jescae.v3i2.981
[35] Mohammad Ridwan, Abdulla Al Shiam, S., Hemel Hossain, Abir, S. I., Shoha, S., Dolon, M. S. A., … Rahman, H. (2024). Navigating a Greener Future: The Role of Geopolitical Risk, Financial Inclusion, and AI Innovation in the BRICS – An Empirical Analysis. *Journal of Environmental Science and Economics*, *3*(1), 78–103. https://doi.org/10.56556/jescae.v3i1.980
[36] Shoha, S., Abdulla Al Shiam, S., Abir, S. I., Dipankar Saha, Shewly Bala, Dolon, M. S. A., … Robeena Bibi. (2024). Towards Carbon Neutrality: The Impact of Private AI Investment and Financial Development in the United States – An Empirical Study Using the STIRPAT Model. *Journal of Environmental Science and Economics*, *3*(4), 59–79. https://doi.org/10.56556/jescae.v3i4.982
[37] Abir, S. I., Shoha, S., Abdulla Al Shiam, S., Dolon, M. S. A., Shewly Bala, Hemel Hossain, … Robeena Bibi. (2024). Enhancing Load Capacity Factor: The Influence of Financial Accessibility, AI Innovation, and Institutional Quality in the United States. *Journal of Environmental Science and Economics*, *3*(4), 12–36. https://doi.org/10.56556/jescae.v3i4.979
[38] Mohammad Ridwan, Bala, S., Shiam, S. A. A., Akhter, A., Asrafuzzaman, M., Shochona, S. A., … Shoha, S. (2024). Leveraging AI for a Greener Future: Exploring the Economic and Financial Impacts on Sustainable Environment in the United States. *Journal of Environmental Science and Economics*, *3*(3), 1–30. https://doi.org/10.56556/jescae.v3i3.970
[39] Akhter, A., Sarder Abdulla Al Shiam, Mohammad Ridwan, Abir, S. I., Shoha, S., Nayeem, M. B., … Robeena Bibi. (2024). Assessing the Impact of Private Investment in AI and Financial Globalization on Load Capacity Factor: Evidence from United States. *Journal of Environmental Science and Economics*, *3*(3), 99–127. https://doi.org/10.56556/jescae.v3i3.977
[40] Sohail,Muhammad Noman and Ren,Jiadong and Muhammad,Musa Uba and Rizwan,Tahir and Iqbal,Wasim and Abir,Shake Ibna. Bio Tech System, Group covariates assessment on real-life diabetes patients by fractional polynomials: a study based on logistic regression modeling, English, Journal article, USA, 1944-3285, 10, Edmond, *Journal of Biotech Research,* (116–125), 2019.
[41] Abir, Shake Ibna, "Parameter Estimation for Stroke Patients Using Brain CT Perfusion Imaging with Deep Temporal Convolutional Neural Network", *Masters Theses & Specialist Projects.* Paper 3755, https://digitalcommons.wku.edu/theses/3755, 2024.
[42] S. I. Abir, S. Shoha, S. A. Al Shiam, M. M. Uddin, M. A. Islam Mamun and S. M. Shamsul Arefeen, "A Comprehensive Examination of MR Image-Based Brain Tumor Detection via Deep Learning Networks," *2024 Sixth International Conference on Intelligent Computing in Data Sciences (ICDS)*, Marrakech, Morocco, pp. 1-8, doi: 10.1109/ICDS62089.2024.10756457, 2024.
[43] S. I. Abir, S. Shoha, S. A. Al Shiam, M. M. Uddin, M. A. Islam Mamun and S. M. Shamsul Arefeen, "Health Risks and Disease Transmission in Undocumented Immigrants in the U.S Using Predictive ML," 2024 Sixth International Conference on Intelligent Computing in Data Sciences (ICDS), Marrakech, Morocco, pp. 1-6, doi: 10.1109/ICDS62089.2024.10756308, 2024.
[44] Abir, S. I., Shaharina Shoha, Sarder Abdulla Al shiam, Nazrul Islam Khan, Abid Hasan Shimanto, Muhammad Zakaria, & S M Shamsul Arefeen. Deep Learning Application of LSTM(P) to predict the risk factors of etiology cardiovascular disease. *Journal of Computer Science and Technology Studies*, *6*(5), 181-200. https://doi.org/10.32996/jcsts.2024.6.5.15, 2024.
[45] Sohail, M. N., Jiadong, R., Irshad, M., Uba, M. M., and Abir, S. I, Data mining techniques for Medical Growth: A Contribution of Researcher reviews, Int. J. Comput. Sci. Netw. Secur, 18, 5-10, 2018.

[46] Shaharina Shoha, Abir, S. I., Sarder Abdulla Al shiam, Md Shah Ali Dolon, Abid Hasan Shimanto, Rafi Muhammad Zakaria, & Md Atikul Islam Mamun. Enhanced Parkinson's Disease Detection Using Advanced Vocal Features and Machine Learning . *Journal of Computer Science and Technology Studies*, *6*(5), 113-128. https://doi.org/10.32996/jcsts.2024.6.5.10, 2024.

[47] Abir, S. I., Shaharina Shoha, Md Miraj Hossain, Syed Moshiur Rahman, Shariar Islam Saimon, Intiser Islam, Md Atikul Islam Mamun, & Nazrul Islam Khan. Deep Learning-Based Classification of Skin Lesions: Enhancing Melanoma Detection through Automated Preprocessing and Data Augmentation. *Journal of Computer Science and Technology Studies*, *6*(5), 152-167. https://doi.org/10.32996/jcsts.2024.6.5.13, 2024.

[48] Abir, S. I., Shaharina Shoha, Md Miraj Hossain, Nigar Sultana, Tui Rani Saha, Mohammad Hasan Sarwer, Shariar Islam Saimon, Intiser Islam, & Mahmud Hasan. (2025). Machine Learning and Deep Learning Techniques for EEG-Based Prediction of Psychiatric Disorders. *Journal of Computer Science and Technology Studies*, *7*(1), 46-63. https://doi.org/10.32996/jcsts.2025.7.1.4

[49] Mohammad Hasan Sarwer, Tui Rani Saha, Abir, S. I., Shaharina Shoha, Md Miraj Hossain, Nigar Sultana, Shariar Islam Saimon, Intiser Islam, Mahmud Hasan, & Sarder Abdulla Al Shiam. (2025). EEG Functional Connectivity and Deep Learning for Automated Diagnosis of Alzheimer's disease and Schizophrenia. *Journal of Computer Science and Technology Studies*, *7*(1), 82-99. https://doi.org/10.32996/jcsts.2025.7.1.7

[50] Abir, S. I., Shahrina Shoha, Sarder Abdulla Al shiam, Md Shah Ali Dolon, Abid Hasan Shimanto, Rafi Muhammad Zakaria, & Md Atikul Islam Mamun. (2024). Deep Neural Networks in Medical Imaging: Advances, Challenges, and Future Directions for Precision Healthcare . *Journal of Computer Science and Technology Studies*, *6*(5), 94-112. https://doi.org/10.32996/jcsts.2024.6.5.9

[51] Shariar Islam Saimon, Intiser Islam, Shake Ibna Abir, Nigar Sultana, Md Sanjit Hossain, & Sarder Abdulla Al Shiam. (2025). Advancing Neurological Disease Prediction through Machine Learning Techniques. *Journal of Computer Science and Technology Studies*, *7*(1), 139-156. https://doi.org/10.32996/jcsts.2025.7.1.11

[52] Nigar Sultana, Shariar Islam Saimon, Intiser Islam, Abir, S. I., Md Sanjit Hossain, Sarder Abdulla Al Shiam, & Nazrul Islam Khan. (2025). Artificial Intelligence in Multi-Disease Medical Diagnostics: An Integrative Approach. *Journal of Computer Science and Technology Studies*, *7*(1), 157-175. https://doi.org/10.32996/jcsts.2025.7.1.12

[53] Abir, S. I., Shaharina Shoha, Sarder Abdulla Al Shiam, Shariar Islam Saimon, Intiser Islam, Md Atikul Islam Mamun, Md Miraj Hossain, Syed Moshiur Rahman, & Nazrul Islam Khan. (2024). Precision Lesion Analysis and Classification in Dermatological Imaging through Advanced Convolutional Architectures. *Journal of Computer Science and Technology Studies*, *6*(5), 168-180. https://doi.org/10.32996/jcsts.2024.6.5.14