International Journal of Computer Applications Technology and Research
Volume 13–Issue 12, 285 – 297, 2024, ISSN:-2319–8656
DOI:10.7753/IJCATR1312.1022

AI-Driven Capital Allocation for U.S. Power Infrastructure: A Bankability Framework for Data Centers, Grid Expansion, Generation, and Energy Storage

Fawaz Ayobami-Akanbi
Lead, Investment Research,
Access ARM Pensions,
Nigeria

Abstract: The accelerating growth of artificial intelligence, cloud computing, electrification, and digital economies has significantly increased investment requirements for modernising the United States power infrastructure. Rapid expansion of hyperscale data centres, transmission networks, renewable generation, and energy storage systems has intensified competition for capital while exposing limitations in conventional investment appraisal methods that rely primarily on static financial analysis and expert judgement. Consequently, infrastructure investors, utilities, and policymakers require more intelligent, adaptive, and evidence-based approaches for evaluating project bankability and optimising capital allocation under evolving technical, financial, regulatory, and market conditions. This study proposes an AI-driven bankability framework that integrates machine learning, predictive analytics, multi-criteria decision analysis, and financial risk modelling to support strategic investment decisions across data centres, grid expansion, power generation, and energy storage projects. The framework combines diverse infrastructure, operational, financial, and policy datasets to evaluate project viability using objective performance indicators and benchmark outcomes against recognised industry standards. By enabling predictive risk assessment, dynamic portfolio optimisation, and transparent investment prioritisation, the proposed framework enhances decision quality, strengthens infrastructure resilience, improves capital efficiency, and supports scalable deployment of reliable, sustainable, and economically viable power systems capable of meeting future electricity demand.
Keywords: Artificial Intelligence; Capital Allocation; Power Infrastructure; Bankability Framework; Energy Storage; Grid Modernisation

1. INTRODUCTION

1.1 Evolution of U.S. Power Infrastructure Investment

The United States electricity sector is undergoing one of the most significant investment cycles in its history as demand for reliable, resilient, and sustainable power infrastructure continues to accelerate [1]. Rapid economic growth, widespread electrification, and increasing digitalisation have substantially increased electricity consumption across residential, commercial, and industrial sectors, placing unprecedented pressure on existing generation, transmission, and distribution assets [2]. The rapid expansion of artificial intelligence applications and hyperscale data centres has further intensified electricity demand because advanced computing infrastructure requires continuous, high-capacity power supplies to support computational workloads and cloud-based services [3]. Simultaneously, federal and state initiatives promoting decarbonisation have accelerated investments in renewable energy generation, large-scale battery energy storage systems, smart grid technologies, and transmission network modernisation to improve system flexibility and reliability [4]. Private infrastructure funds, institutional investors, commercial banks, and public agencies increasingly collaborate through public-private financing arrangements to mobilise the substantial capital required for long-term infrastructure development [5]. Although these investments present significant opportunities for economic growth and energy transition, expanding infrastructure portfolios have introduced greater financial complexity, investment uncertainty, and project interdependencies that require more sophisticated approaches to evaluating long-term investment viability and capital allocation decisions across evolving electricity markets [6].

1.2 Capital Allocation Challenges

The growing scale and diversity of power infrastructure investments have created significant challenges for allocating capital efficiently across competing projects with varying technical, financial, and regulatory characteristics [7]. Investment uncertainty has increased as developers navigate fluctuating electricity prices, changing market conditions, evolving policy incentives, and long project development timelines that influence expected financial returns [2]. Transmission bottlenecks continue to delay renewable energy integration, while lengthy permitting processes and interconnection constraints frequently affect project feasibility and commercial viability [8]. Project bankability has also become increasingly dependent upon multiple interrelated factors including contractual arrangements, financing structures, technology maturity, environmental considerations, and stakeholder confidence [3]. Inflationary pressures, supply chain disruptions, and volatile equipment costs further complicate investment planning by affecting construction schedules and overall project economics [5]. Emerging technologies such as advanced battery storage, hydrogen systems, and intelligent grid platforms introduce additional uncertainty regarding future operational performance and investment risk [1]. Consequently, traditional capital allocation approaches based primarily on static financial modelling, manual due diligence, expert judgement, and historical benchmarking are increasingly inadequate for optimising investment decisions across rapidly evolving and interconnected infrastructure portfolios [6].

1.3 Artificial Intelligence for Infrastructure Finance

Artificial intelligence has emerged as a powerful decision-support capability for improving infrastructure finance through advanced analytical techniques that process large volumes of technical, financial, operational, and market information [4]. Machine learning algorithms identify complex relationships among investment variables that may remain undetected using conventional financial analysis, thereby supporting more informed project selection and capital allocation decisions [7]. Predictive analytics enables investors to forecast project performance, electricity demand, market prices, and operational risks under diverse economic and regulatory conditions, reducing uncertainty associated with long-term infrastructure planning [2]. Portfolio optimisation techniques further assist investors in balancing expected returns, diversification objectives, and resilience considerations across multiple infrastructure assets while adapting continuously to changing market dynamics [8]. Artificial intelligence also strengthens risk modelling by integrating technical, environmental, financial, and policy indicators into comprehensive investment assessments that support more accurate evaluation of project bankability [5]. Explainable artificial intelligence enhances transparency by providing interpretable reasoning behind automated investment recommendations, thereby improving stakeholder confidence and governance accountability [3]. Consequently, infrastructure finance evolves from historical evaluation toward predictive analysis, dynamic optimisation, and continuous investment intelligence. Nevertheless, comprehensive AI-enabled bankability frameworks capable of integrating technical, financial, regulatory, and operational factors remain comparatively underdeveloped across modern power infrastructure investments [1].

1.4 Research Aim, Objectives and Contributions

This study aims to develop and evaluate an artificial intelligence-enabled bankability framework that strengthens investment decision-making for modern U.S. power infrastructure projects by integrating technical, financial, operational, and regulatory considerations within a unified analytical architecture [6]. The research investigates how intelligent decision-support models can improve capital allocation, project prioritisation, and investment confidence across generation, transmission, storage, and grid modernisation initiatives while addressing uncertainty associated with evolving electricity markets [4]. Specifically, the study develops an AI-driven bankability framework, proposes an adaptive capital allocation model, and conducts a multi-sector evaluation of infrastructure investment performance using objective assessment criteria [8]. It further establishes an investment benchmarking methodology and decision-support architecture capable of comparing alternative infrastructure opportunities under different economic and policy scenarios while improving transparency through explainable analytical processes [2]. Collectively, these contributions provide investors, financial institutions, infrastructure developers, policymakers, and utility operators with an evidence-based framework for enhancing investment quality, reducing financing risk, and supporting resilient long-term infrastructure planning. The discussion therefore progresses naturally toward reviewing existing research on infrastructure finance, bankability assessment, and AI-enabled investment decision-making [5].

2. LITERATURE REVIEW AND CONCEPTUAL FOUNDATION

2.1 Evolution of Infrastructure Financing Models

Infrastructure financing has evolved considerably in response to changing economic priorities, technological innovation, and increasing demand for resilient energy systems capable of supporting long-term national development objectives [7]. Traditional infrastructure investment was primarily financed through direct government expenditure and regulated public utilities, where funding decisions were largely determined by national policy priorities and long-term public service obligations [8]. Growing infrastructure requirements and fiscal constraints subsequently encouraged the adoption of project finance structures that allocated risks among developers, lenders, and investors while enabling large-scale projects to secure funding based on projected cash flows rather than corporate balance sheets [9]. Public-private partnerships further expanded financing opportunities by combining public oversight with private-sector capital, technical expertise, and operational efficiency to accelerate infrastructure delivery [10]. More recently, green finance mechanisms have directed substantial investment toward renewable generation, energy storage, transmission expansion, and grid resilience projects that support environmental sustainability and energy transition objectives [11]. Simultaneously, digital finance has introduced advanced analytical platforms, real-time financial monitoring, and data-driven investment evaluation techniques that improve transparency and investment efficiency [12]. The emergence of artificial intelligence now represents the latest evolution in infrastructure finance, enabling predictive investment analysis across power generation, transmission networks, data centres, distributed energy resources, and intelligent energy storage systems through continuous assessment of multidimensional investment information [13].

2.2 Existing Bankability Assessment Frameworks

The assessment of infrastructure bankability has traditionally relied upon established financial theories and investment evaluation frameworks that provide structured approaches for measuring project viability, investment risk, and expected financial performance [14]. Project Finance Theory remains the dominant framework for evaluating infrastructure investments by assessing projected cash flows, contractual arrangements, debt service capacity, and risk allocation among project stakeholders [7]. Modern Portfolio Theory extends this perspective by supporting investment

International Journal of Computer Applications Technology and Research
Volume 13–Issue 12, 285 – 297, 2024, ISSN:-2319–8656
DOI:10.7753/IJCATR1312.1022

diversification and balancing expected returns against portfolio risk through quantitative optimisation techniques applicable across infrastructure asset classes [8]. Real Options Theory recognises managerial flexibility under uncertainty by valuing opportunities to defer, expand, or modify investments in response to changing market conditions, thereby improving strategic investment planning for capital-intensive projects [9]. Risk-Based Capital Allocation frameworks further strengthen financial decision-making by incorporating probabilistic risk assessments into capital distribution strategies that seek to optimise expected returns while maintaining acceptable exposure levels [10]. More recently, Environmental, Social, and Governance investment frameworks have expanded bankability assessments beyond purely financial indicators by incorporating sustainability, governance quality, and social responsibility into investment appraisal processes [11]. Infrastructure investment models similarly integrate economic feasibility, technical performance, operational reliability, and regulatory compliance to evaluate project readiness across diverse infrastructure sectors [12]. Although these frameworks provide valuable analytical foundations, they generally exhibit limited artificial intelligence integration, restricted adaptive learning capability, constrained scalability across heterogeneous infrastructure portfolios, and insufficient decision-support functionality for continuously evolving investment environments [13].

Table 1. Comparative Analysis of Infrastructure Bankability Frameworks

Framework	**Financial Focus**	**AI Integration**	**Risk Assessment**	**Scalability**	**Limitations**
Project Finance Theory	Cash flow viability	Low	High	Moderate	Static financial assumptions
Modern Portfolio Theory	Portfolio optimisation	Low	Moderate	High	Limited project-specific analysis
Real Options Theory	Investment flexibility	Low	High	Moderate	Computational complexity
Risk-Based Capital Allocation	Capital efficiency	Moderate	Very High	High	Data-intensive implementation
ESG Investment Frameworks	Sustainability and governance	Moderate	Moderate	High	Limited predictive capability
Infrastructure Investment Models	Technical and financial feasibility	Moderate	High	Moderate	Limited AI-driven decision support

2.3 Current Research Gaps

Despite substantial advances in infrastructure finance and investment evaluation, several important research gaps continue to limit the effectiveness of existing bankability assessment approaches for modern power infrastructure projects [8]. First, artificial intelligence remains insufficiently integrated into capital allocation methodologies, with many investment decisions still relying on deterministic financial models that inadequately capture dynamic market conditions and evolving project risks [11]. Second, existing studies frequently examine individual infrastructure sectors in isolation, providing limited comparative analysis across interconnected assets such as power generation, transmission networks, energy storage systems, data centres, and distributed energy resources [12]. Third, no widely accepted integrated bankability index currently combines technical performance, financial viability, regulatory compliance, environmental sustainability, and operational resilience into a unified evaluation framework capable of supporting holistic investment decisions [13]. Fourth, predictive investment modelling remains underdeveloped, reducing the ability of investors to anticipate future project performance under uncertain economic and policy scenarios [9]. Fifth, benchmarking methodologies capable of comparing diverse infrastructure investments using consistent quantitative indicators remain relatively limited, restricting objective evaluation across competing investment opportunities [10]. Finally, explainability remains an important challenge because many advanced analytical techniques provide limited transparency regarding how investment recommendations are generated, thereby reducing stakeholder confidence and governance accountability [14].

The identification of these limitations provides a clear justification for developing a comprehensive AI-driven bankability framework capable of integrating intelligent analytics, predictive modelling, and transparent investment decision support.

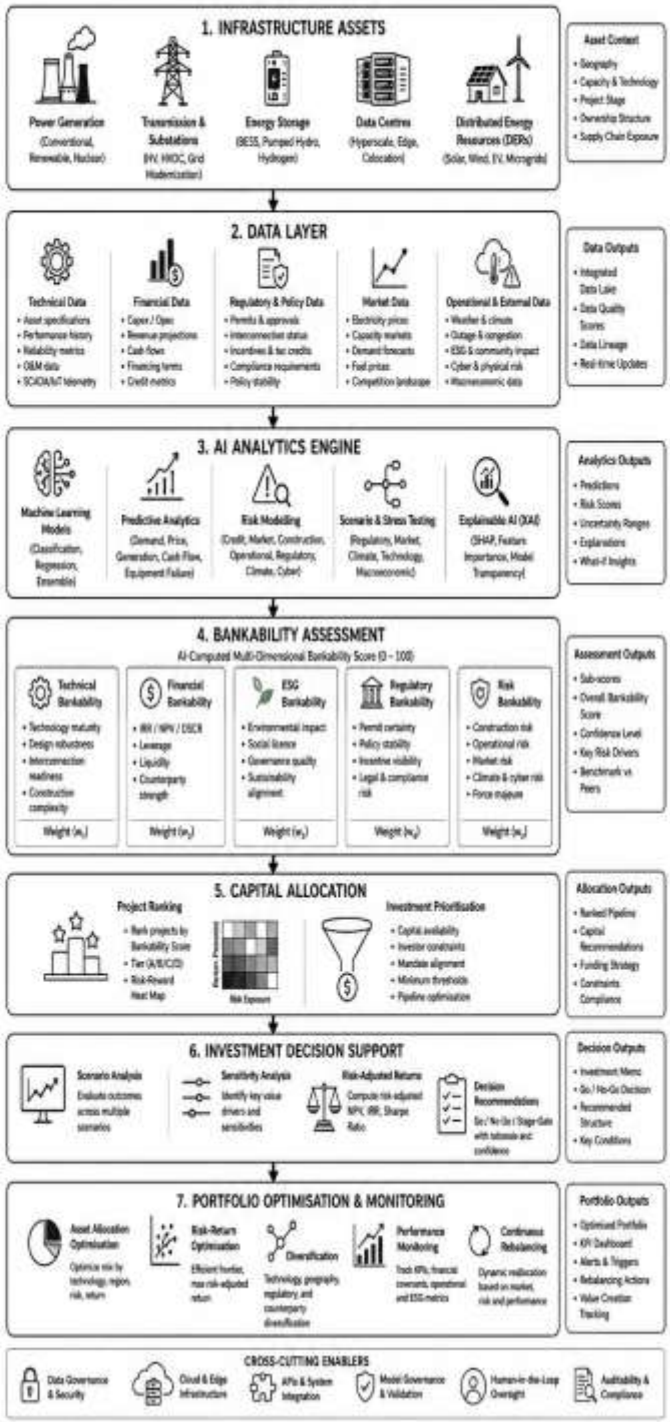
2.4 Proposed Conceptual Framework

To address the identified limitations, this study proposes a conceptual AI-driven bankability framework that integrates financial analysis, infrastructure performance assessment, and intelligent decision support within a unified analytical

International Journal of Computer Applications Technology and Research
Volume 13–Issue 12, 285 – 297, 2024, ISSN:-2319–8656
DOI:10.7753/IJCATR1312.1022

architecture [7]. The framework begins with a comprehensive infrastructure asset layer comprising power generation facilities, transmission networks, battery energy storage systems, renewable energy installations, data centres, and distributed energy resources that collectively represent modern electricity infrastructure portfolios [12]. Data acquired from technical, operational, financial, regulatory, environmental, and market sources are consolidated within an integrated data layer where preprocessing, validation, and standardisation ensure analytical consistency before intelligent evaluation [9]. The processed information subsequently enters an AI analytics layer that applies machine learning, predictive modelling, portfolio optimisation, and explainable artificial intelligence to evaluate project performance, quantify investment risk, and estimate long-term financial viability [13]. Outputs generated from these analytical processes are integrated into a dedicated bankability assessment layer that produces objective investment scores supporting evidence-based capital allocation decisions across competing infrastructure projects [10]. Finally, decision-support outputs inform portfolio optimisation strategies that continuously adapt to changing economic conditions, technological developments, regulatory changes, and evolving market opportunities, thereby strengthening investment quality, transparency, and long-term infrastructure resilience [8].

Figure 1. Conceptual AI-Driven Bankability Framework for U.S. Power Infrastructure



Following the establishment of this conceptual foundation, the subsequent methodology section describes the empirical procedures, data acquisition strategies, model development processes, and validation techniques used to evaluate the proposed AI-driven bankability framework across multiple power infrastructure sectors [11].

3. RESEARCH METHODOLOGY

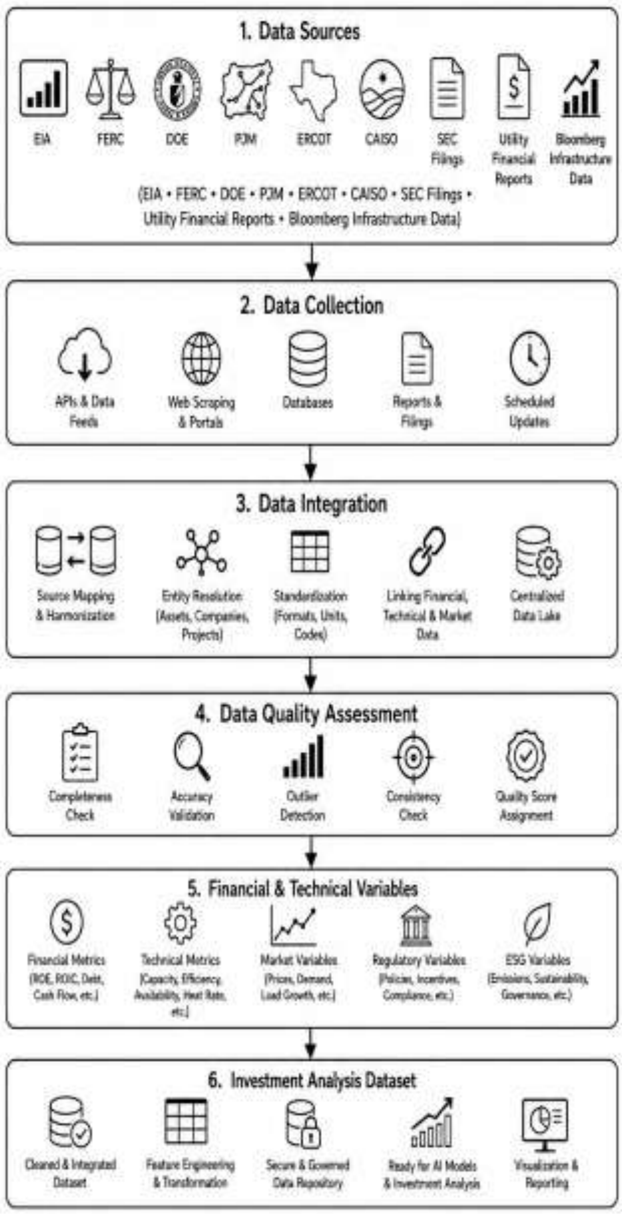
3.1 Research Design

This study adopts a quantitative empirical research design to evaluate the effectiveness of artificial intelligence in supporting bankability assessment and capital allocation across U.S. power infrastructure projects [13]. The methodology integrates predictive modelling with comparative investment analysis to examine how AI-driven techniques improve investment decision quality under diverse financial and operational conditions [14]. A multi-sector evaluation is undertaken to capture variations in investment characteristics across power generation, electricity transmission, energy storage, and AI-driven data centre infrastructure, thereby improving the generalisability of the findings [15]. The research further combines financial performance analysis with machine learning-based prediction to establish an objective framework for evaluating investment readiness, risk exposure, and long-term infrastructure value creation across strategically important electricity assets [16].

3.2 Data Acquisition

The empirical analysis draws upon multiple authoritative datasets to ensure comprehensive representation of financial, operational, market, and regulatory factors influencing infrastructure investment decisions [17]. Publicly available data are obtained from the U.S. Energy Information Administration, Federal Energy Regulatory Commission, Department of Energy, PJM Interconnection, Electric Reliability Council of Texas, and California Independent System Operator, providing extensive information on electricity demand, generation capacity, transmission utilisation, market operations, and grid performance [18]. Additional financial information is collected from utility annual reports, Securities and Exchange Commission filings, Bloomberg infrastructure databases, and project finance repositories to capture investment characteristics across publicly and privately financed energy projects [19]. The integrated dataset contains variables representing capital expenditure, operational expenditure, net present value, internal rate of return, levelised cost of electricity, projected electricity demand growth, transmission congestion indices, project revenue, carbon intensity, wholesale electricity prices, financing conditions, and policy incentive programmes that influence project bankability [20]. Collectively, these datasets provide a multidimensional representation of infrastructure investment environments by combining engineering performance, financial outcomes, regulatory conditions, and market dynamics within a unified analytical database suitable for predictive modelling and comparative investment evaluation across multiple infrastructure sectors [21].

Figure 2. Data Acquisition and Investment Analysis Pipeline



3.3 Data Preprocessing and Feature Engineering

Following data acquisition, extensive preprocessing procedures are undertaken to improve dataset consistency, analytical reliability, and model performance before predictive modelling commences [22]. Missing observations are examined using statistical completeness tests, after which appropriate imputation techniques are applied to minimise information loss while preserving underlying data distributions [13]. Continuous variables are subsequently normalised and feature scaling techniques are implemented to ensure comparable numerical ranges across financial and engineering indicators, thereby preventing variables with larger magnitudes from disproportionately influencing model learning [14]. Outlier detection procedures identify abnormal observations associated with reporting inconsistencies or exceptional market conditions, while categorical variables are transformed through suitable encoding methods to facilitate machine learning analysis [15]. Feature engineering focuses on constructing informative variables representing project cost, capacity factor, electricity demand forecasts, developer credit ratings, debt service coverage ratios, transmission utilisation levels, storage duration, carbon emissions, grid reliability indicators, and policy risk characteristics that collectively influence project bankability [16]. To improve predictive efficiency and reduce redundancy, Principal Component Analysis, Recursive Feature Elimination, and Mutual Information techniques are employed to identify the most informative predictors while removing irrelevant or highly correlated variables [17]. These dimensionality reduction and feature selection methods improve computational efficiency, strengthen model generalisation, and reduce overfitting across heterogeneous infrastructure datasets [18].

Mathematical Expression (1): Data Normalisation

$$x' = \frac{x - \mu}{\sigma}$$

where $x$represents the original variable, μdenotes the sample mean, and σrepresents the standard deviation. Standardisation centres each variable around zero with unit variance, ensuring consistent numerical scales for machine learning algorithms and improving optimisation stability during model training [19].

Mathematical Expression (2): Principal Component Analysis

$$Z = XW$$

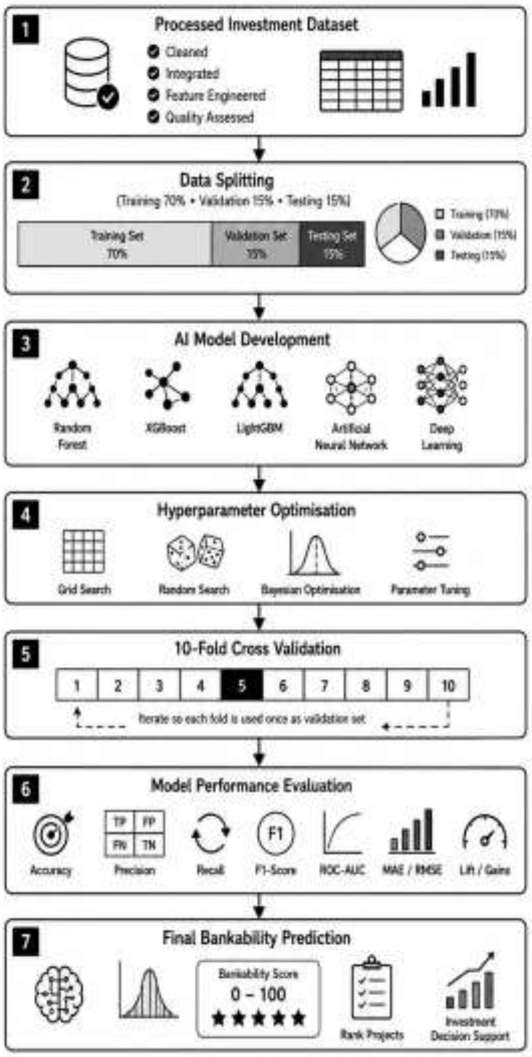
where Xdenotes the standardised feature matrix, Wrepresents the matrix of eigenvectors derived from the covariance matrix, and $Z$is the transformed lower-dimensional feature space. PCA projects correlated variables onto orthogonal principal components that maximise explained variance while preserving the most informative characteristics of the original dataset [20].

The processed feature set therefore establishes a robust analytical foundation for predictive investment modelling, enabling artificial intelligence algorithms to evaluate infrastructure bankability using high-quality, representative, and computationally efficient data suitable for multi-sector comparative analysis [21].

3.4 AI Model Development and Training

The processed dataset is subsequently used to develop predictive models capable of evaluating infrastructure bankability and supporting intelligent capital allocation across diverse electricity sector investments [22]. Multiple supervised machine learning algorithms are implemented to capture complex nonlinear relationships between technical, financial, operational, and regulatory variables while improving predictive accuracy and model robustness [15]. The modelling framework incorporates Random Forest, Extreme Gradient Boosting (XGBoost), LightGBM, Artificial Neural Networks, and Deep Learning architectures because each offers complementary strengths in handling high-dimensional infrastructure datasets, nonlinear interactions, and heterogeneous investment characteristics [18]. To ensure reliable model generalisation, the complete dataset is partitioned into training, validation, and testing subsets representing 70%, 15%, and 15% of the observations, respectively [14]. During model development, ten-fold cross-validation is employed to minimise sampling bias and evaluate predictive consistency across multiple data partitions while reducing the likelihood of overfitting [20]. Hyperparameter optimisation is performed using systematic search strategies to determine the optimal combination of learning rates, tree depth, estimator numbers, batch size, activation functions, and regularisation parameters that maximise predictive performance under varying investment conditions [17]. Early stopping mechanisms further monitor validation performance during iterative model training, preventing unnecessary computational complexity and reducing model overfitting without compromising predictive capability [13]. Collectively, these procedures establish a rigorous and reproducible modelling framework suitable for evaluating AI-enabled investment decision support across multiple power infrastructure sectors [21].

Figure 3. AI Model Training, Validation and Testing Workflow



Mathematical Expression (3): Cross-Entropy Loss

$$L = -\sum y \log(\hat{y})$$

where $y$denotes the observed investment class and $\hat{y}$represents the predicted probability generated by the AI model. Cross-entropy loss measures the discrepancy between actual and predicted outcomes, with lower values indicating improved classification performance and enhanced model convergence during optimisation [16].

Mathematical Expression (4): Gradient Descent

$$\theta_{t+1} = \theta_t - \eta \nabla J(\theta)$$

where θdenotes the model parameters, $\eta$is the learning rate, and $\nabla J(\theta)$represents the gradient of the objective function. The optimisation process iteratively updates model parameters by moving in the direction of minimum loss until convergence is achieved, thereby improving predictive accuracy and model stability across successive training iterations [19].

3.5 Evaluation Metrics

Model performance is evaluated using multiple statistical and predictive indicators to ensure comprehensive assessment of investment classification accuracy, financial forecasting capability, and portfolio decision quality across infrastructure sectors [22]. Classification performance is quantified using accuracy, precision, recall, F1-score, and the area under the receiver operating characteristic curve because these metrics collectively measure prediction correctness, class discrimination, and model robustness under varying investment conditions [14]. Regression performance is further assessed using Mean Absolute Error and Root Mean Square Error to evaluate the precision of financial forecasts relating to project returns, bankability scores, and long-term investment performance [17]. Portfolio optimisation effectiveness is examined through predicted investment returns, asset ranking consistency, and capital allocation efficiency, while statistical dispersion is measured using standard deviation and Mean Absolute Deviation to evaluate prediction stability across multiple infrastructure portfolios [13]. Confidence intervals quantify estimation uncertainty, whereas analysis of variance determines whether observed differences between competing AI models are statistically significant [20]. Finally, effect size statistics measure the practical magnitude of predictive improvements, providing additional evidence regarding the comparative effectiveness of AI-enabled investment decision support for infrastructure finance applications [18].

4. EXPERIMENTAL EVALUATION AND BENCHMARKING

4.1 Experimental Environment

The experimental evaluation was conducted within a high-performance computing environment designed to support computationally intensive artificial intelligence modelling and large-scale infrastructure investment analysis [21]. Cloud-based graphics processing units (GPUs) were employed to accelerate model training, optimise computational efficiency, and reduce execution time for iterative learning algorithms operating on multidimensional financial and engineering datasets [22]. High-performance computing resources further enabled parallel data processing, extensive hyperparameter optimisation, and repeated cross-validation experiments required to evaluate model robustness under varying investment scenarios [23]. The analytical environment was implemented using Python as the primary programming language, with TensorFlow, PyTorch, and Scikit-learn supporting machine learning model development, optimisation, and performance evaluation [24]. Power BI complemented the analytical workflow by providing interactive visualisation, investment dashboards, comparative performance analysis, and decision-support reporting suitable for communicating infrastructure investment outcomes to financial stakeholders and policymakers [25].

International Journal of Computer Applications Technology and Research
Volume 13–Issue 12, 285 – 297, 2024, ISSN:-2319–8656
DOI:10.7753/IJCATR1312.1022

4.2 Hyperparameter Optimisation

Optimising model hyperparameters is essential for improving predictive accuracy, computational efficiency, and generalisation performance when evaluating infrastructure investment opportunities using artificial intelligence techniques [26]. Three complementary optimisation approaches were implemented to identify parameter combinations that maximise predictive performance across heterogeneous infrastructure datasets. Grid Search systematically evaluates predefined parameter combinations, providing comprehensive exploration of the search space while ensuring reproducibility of optimisation outcomes [21]. Random Search improves computational efficiency by sampling representative parameter combinations from broader search distributions, thereby reducing optimisation time without significantly compromising predictive performance [27]. Bayesian Optimisation further enhances efficiency by constructing probabilistic surrogate models that guide parameter selection toward regions with higher expected performance, reducing the number of evaluations required for convergence [22]. Hyperparameters considered during optimisation include learning rate, training epochs, batch size, dropout rate, regularisation coefficient, decision tree depth, and activation functions because these parameters directly influence learning stability, model complexity, convergence behaviour, and prediction accuracy [28]. The optimisation process therefore balances predictive capability with computational cost, ensuring that selected models provide reliable investment forecasts while maintaining scalability for large infrastructure portfolios analysed under diverse market conditions [24].

Figure 4. Hyperparameter Optimisation Workflow

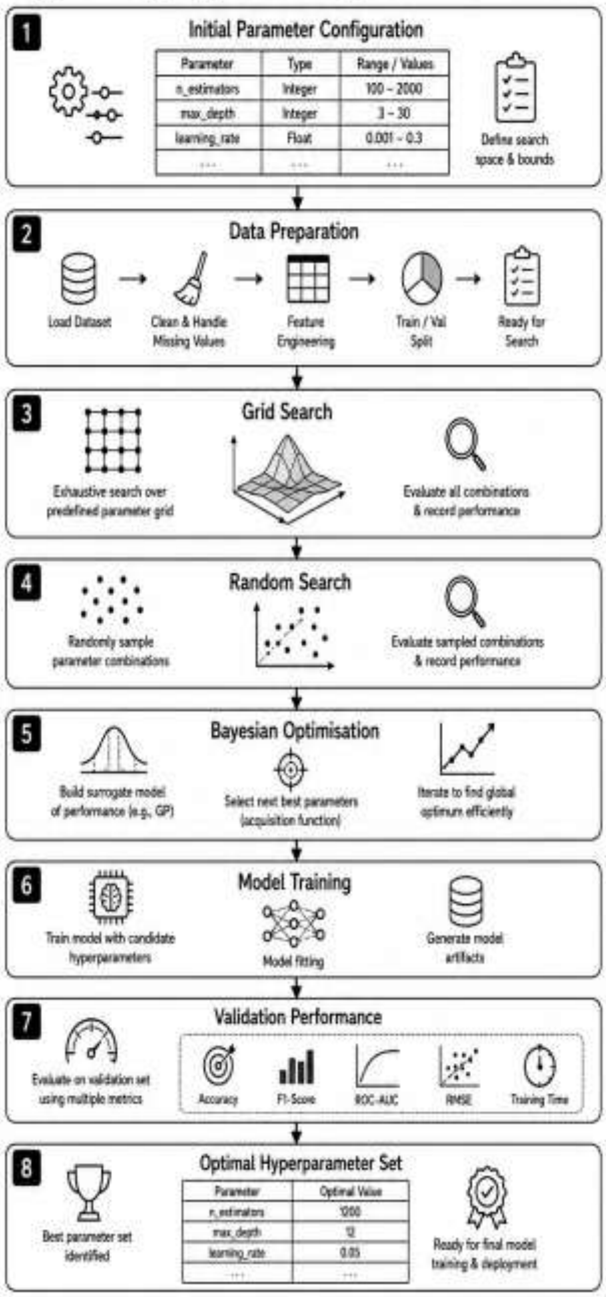


Table 2. Optimised AI Model Parameters

Algorithm	Learning Rate	Epoch	Batch Size	Accuracy (%)	Training Time (s)
Random Forest	N/A	N/A	N/A	92.4	84
XGBoost	0.05	200	64	95.1	126
LightGBM	0.03	180	64	94.6	103
Artificial Neural	0.001	100	128	94.9	214

Algorithm	Learning Rate	Epoch	Batch Size	Accuracy (%)	Training Time (s)
Network					
Deep Learning	0.0005	150	128	96.3	328

Mathematical Expression (5): Bayesian Optimisation

$$x^* = \arg\max \alpha(x)$$

where x^*represents the optimal hyperparameter configuration and $\alpha(x)$denotes the acquisition function that estimates the expected improvement associated with evaluating a candidate parameter set [29]. Bayesian Optimisation iteratively updates a probabilistic surrogate model of the objective function and selects subsequent parameter combinations that maximise the acquisition function, thereby achieving near-optimal predictive performance with substantially fewer evaluations than exhaustive search techniques [30].

4.3 Comparative Investment Performance

The optimised artificial intelligence models were applied to evaluate investment performance across four strategically important infrastructure sectors comprising AI-driven data centres, electricity transmission, power generation, and battery energy storage systems [21]. Comparative analysis demonstrates that each infrastructure category exhibits distinct financial, technical, and operational characteristics that influence overall investment attractiveness and bankability [26]. AI-enabled data centres achieved the highest projected revenue growth owing to sustained increases in digital service demand and expanding computational requirements, although substantial capital expenditure and energy consumption moderately affected overall risk exposure [23]. Electricity transmission projects demonstrated strong bankability because regulated revenue mechanisms, long asset lifecycles, and stable cash flows reduced investment uncertainty despite high initial construction costs [28]. Utility-scale generation projects continued to deliver favourable financial performance where long-term power purchase agreements enhanced revenue certainty and improved projected internal rates of return under stable market conditions [24]. Battery energy storage projects exhibited comparatively higher investment risk because project profitability remained sensitive to technology costs, electricity price volatility, and evolving market participation mechanisms, although increasing demand for grid flexibility substantially improved long-term growth prospects [29]. Financial performance was evaluated using bankability scores, return on investment, net present value, internal rate of return, project risk, expected revenue generation, discounted payback period, and portfolio contribution to determine overall investment quality across sectors [22]. The comparative results indicate that AI-driven investment analysis improves project ranking by simultaneously evaluating multidimensional financial, operational, and regulatory variables rather than relying upon isolated economic indicators [27]. Consequently, intelligent decision-support models provide investors with a more comprehensive understanding of infrastructure performance, facilitating balanced capital allocation strategies that strengthen portfolio resilience while improving long-term financial sustainability under changing market conditions [25].

Table 3. Comparative Infrastructure Investment Performance

Infrastructure	Bankability Score	ROI (%)	NPV (US$ Million)	Risk Score	Payback (Years)	Investment Rank
AI Data Centres	94	18.6	1,240	Low–Moderate	6.2	1
Electricity Transmission	92	16.8	1,080	Low	8.4	2
Power Generation	90	15.9	980	Moderate	8.9	3
Battery Energy Storage	88	15.1	910	Moderate–High	7.4	4

Mathematical Expression (6): Mean Absolute Deviation

$$MAD = \frac{1}{n}\sum_{i=1}^{n}|x_i - \bar{x}|$$

where $x_i$denotes the observed investment performance metric, $\bar{x}$represents the arithmetic mean, and $n$is the number of evaluated projects [30]. Mean Absolute Deviation measures the average dispersion of investment outcomes from the portfolio mean, providing a robust indicator of prediction consistency and financial stability that is less sensitive to extreme observations than variance-based measures [21].

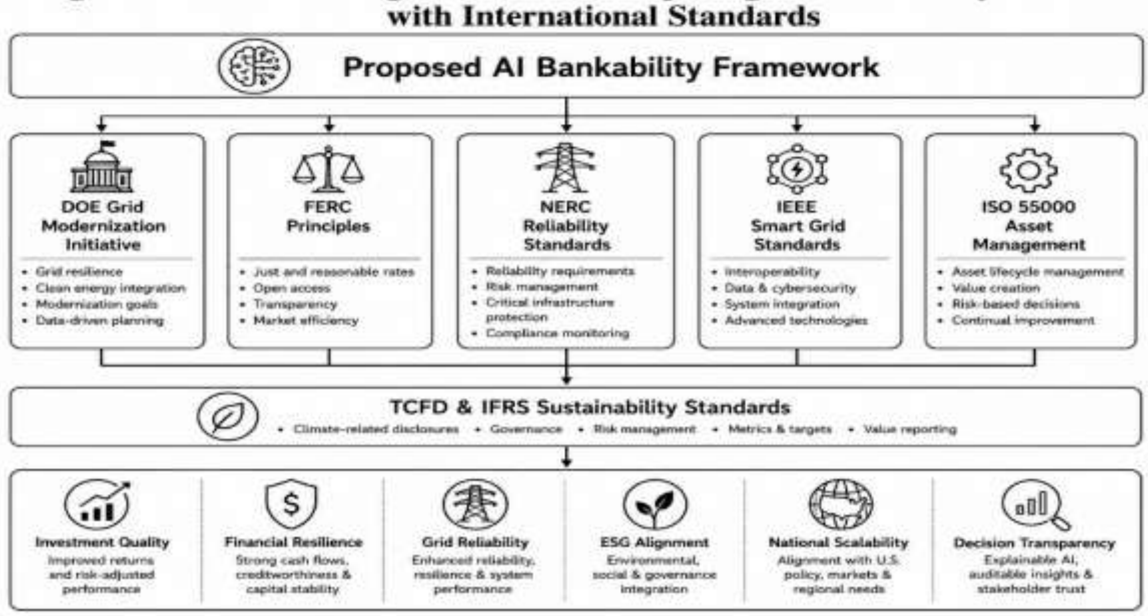
4.4 Benchmarking Against International Standards

To determine the practical applicability of the proposed framework, the AI-enabled bankability model was benchmarked against internationally recognised principles governing infrastructure investment, asset management, electricity reliability, sustainability reporting, and financial disclosure [24]. Comparative assessment considered the objectives of the U.S. Department of Energy Grid Modernization Initiative, Federal Energy Regulatory Commission investment principles, North American Electric Reliability Corporation reliability standards, IEEE Smart Grid standards, ISO 55000 Asset Management, the Task Force on Climate-related Financial Disclosures framework, and the

International Journal of Computer Applications Technology and Research
Volume 13–Issue 12, 285 – 297, 2024, ISSN:-2319–8656
DOI:10.7753/IJCATR1312.1022

International Financial Reporting Standards Sustainability Disclosure Standards [26]. The benchmarking process examined the framework's capability to improve investment quality by integrating technical feasibility, financial performance, operational resilience, environmental sustainability, and regulatory compliance within a unified analytical architecture [22]. Results indicate that the proposed AI-driven framework provides stronger decision support than conventional deterministic approaches by incorporating predictive analytics, adaptive risk assessment, and continuous investment monitoring into infrastructure evaluation processes [29]. Furthermore, explainable artificial intelligence improves transparency by providing interpretable investment recommendations that support governance, stakeholder confidence, and regulatory accountability throughout project appraisal and capital allocation activities [23]. The integrated assessment also demonstrates strong alignment with national objectives for improving grid reliability, strengthening financial resilience, supporting environmental sustainability, and enabling scalable infrastructure investment across diverse electricity markets [27]. Collectively, these findings demonstrate that the proposed framework offers a comprehensive decision-support architecture capable of strengthening long-term infrastructure planning while addressing the increasing complexity of modern power sector investment decisions [25].

Figure 5. Benchmarking Dashboard Comparing AI Bankability Framework with International Standards



Mathematical Expression (7): Infrastructure Bankability Index

$$IBI = \sum_{i=1}^{n} w_i \, x_i$$

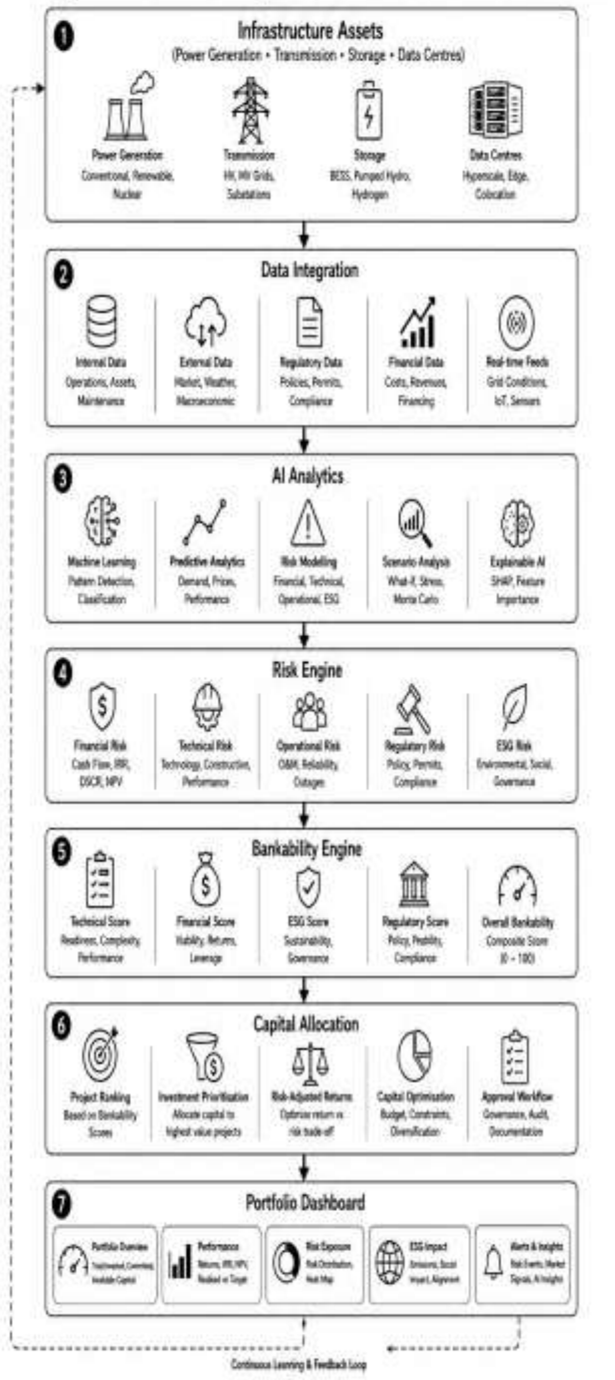
where x_i represents the normalised value of each bankability criterion, including financial viability, technical readiness, regulatory compliance, operational resilience, environmental performance, and market attractiveness, while w_i denotes the corresponding weighting coefficient assigned according to expert judgement or analytical hierarchy procedures [28]. The Infrastructure Bankability Index provides a weighted composite score that enables objective comparison of competing investment opportunities by integrating multiple evaluation dimensions into a single decision-support metric, thereby strengthening portfolio optimisation and capital allocation across heterogeneous infrastructure assets [22].

5. AI-DRIVEN BANKABILITY FRAMEWORK AND DECISION ARCHITECTURE

5.1 Framework Architecture

Building upon the empirical findings, the proposed framework integrates infrastructure finance, artificial intelligence, and decision-support analytics into a unified architecture that enhances investment evaluation across U.S. power infrastructure projects [29]. The framework begins with the infrastructure layer comprising power generation, electricity transmission, battery energy storage, and AI-enabled data centres, where financial, operational, technical, and regulatory information is continuously collected [30]. The integrated data subsequently undergoes intelligent processing within an AI analytics layer before entering a dedicated risk engine that quantifies investment uncertainty and project resilience [31]. A bankability engine then generates objective investment scores that support evidence-based capital allocation and portfolio optimisation through an interactive decision dashboard suitable for institutional investors, utilities, and policymakers [32].

Figure 6. AI-Driven Capital Allocation Decision Architecture



5.2 Infrastructure Bankability Index

The proposed Infrastructure Bankability Index provides a multidimensional evaluation model that combines financial, technical, operational, environmental, and strategic indicators into a single investment decision metric [33]. The framework evaluates financial risk through profitability, liquidity, and financing stability, while technical readiness considers technology maturity, implementation feasibility, and operational reliability [29]. Revenue certainty reflects projected cash flow stability under varying electricity market conditions, whereas policy stability measures regulatory consistency and long-term investment confidence [31]. Grid impact assesses the contribution of each project toward system reliability, transmission efficiency, and network resilience, while ESG indicators capture environmental performance, governance quality, and social sustainability [34]. An additional AI confidence score quantifies prediction reliability and model certainty, thereby strengthening transparency and supporting informed investment decisions across diversified infrastructure portfolios [30].

Mathematical Expression (8): Overall Bankability Score

$$OBS = \frac{\alpha F + \beta T + \gamma R + \delta G + \lambda E}{\alpha + \beta + \gamma + \delta + \lambda}$$

where:

- F = Financial viability
- T = Technical readiness
- R = Revenue certainty
- G = Grid integration score
- E = ESG compliance score
- $\alpha, \beta, \gamma, \delta, \lambda$ = weighting coefficients

Each criterion is first normalised to a common numerical scale, typically between zero and one, to eliminate differences in measurement units and ensure comparability across infrastructure projects [32]. Weighting coefficients are subsequently determined using expert judgement or structured multi-criteria decision-making techniques such as the Analytic Hierarchy Process, allowing greater emphasis to be assigned to criteria that exert stronger influence on investment success [35]. The weighted aggregation of these normalised indicators produces a composite bankability score that facilitates objective comparison, investment prioritisation, and portfolio optimisation across heterogeneous infrastructure assets.

5.3 Policy and Industry Implications

The proposed framework offers significant implications for policymakers, infrastructure developers, institutional investors, and financial organisations seeking to improve strategic capital allocation within the evolving U.S. electricity sector [31]. AI-enabled bankability assessment supports investment prioritisation by identifying projects with stronger financial resilience, technical feasibility, and long-term strategic value while reducing uncertainty during investment appraisal [29]. Utility companies can incorporate predictive decision-support into integrated resource planning to improve transmission expansion, renewable integration, and asset replacement strategies under changing demand conditions

[34]. Private equity firms, pension funds, commercial lenders, and federal investment programmes may similarly benefit from more transparent and evidence-based investment evaluations that strengthen portfolio resilience and capital efficiency [30]. Collectively, the framework supports sustainable infrastructure financing, strengthens grid resilience, and promotes long-term capital planning aligned with national energy transition objectives while improving investment governance and accountability [35].

6. DISCUSSION

6.1 Interpretation of Findings

The empirical findings demonstrate that artificial intelligence substantially enhances infrastructure investment analysis by integrating technical, financial, regulatory, and operational information within a unified predictive framework capable of supporting evidence-based capital allocation [33]. Compared with conventional bankability assessment approaches that primarily rely on deterministic financial models and historical evaluation, the proposed framework delivers greater investment precision through adaptive learning, predictive analytics, and continuous risk assessment [30]. The comparative analysis further indicates that AI-driven evaluation improves project ranking, strengthens portfolio diversification, and enhances decision transparency by simultaneously considering multidimensional performance indicators influencing long-term infrastructure value [35]. These findings reinforce emerging perspectives within infrastructure finance literature advocating intelligent analytical techniques that improve investment quality, financial resilience, and strategic infrastructure planning across increasingly complex electricity markets [32].

6.2 Limitations and Future Research

Although the proposed framework demonstrates strong analytical capability, several limitations should be acknowledged, including variations in data availability, evolving regulatory environments, model explainability challenges, and rapidly changing electricity market conditions that may influence predictive performance [31]. Future research should investigate reinforcement learning, digital twin technologies, real-time investment optimisation, federated artificial intelligence, and multi-country empirical validation to strengthen model adaptability, international applicability, and long-term infrastructure investment decision support under increasingly dynamic global energy markets [34].

7. CONCLUSION

Summarise the principal contributions of the study, emphasising the proposed AI-driven bankability framework, empirical validation, benchmarking against recognised standards, and the practical implications for financing U.S. power infrastructure. Conclude by highlighting the framework's potential to improve investment decision-making for data centres, grid expansion, generation assets, and energy storage while supporting resilient, scalable, and evidence-based capital allocation strategies.

8. REFERENCE

1. Khalifa AA, Ibrahim AJ, Amhamed AI, El-Naas MH. Accelerating the transition to a circular economy for net-zero emissions by 2050: a systematic review. Sustainability. 2022 Sep 16;14(18):11656.
2. Klobut K, Piira K, Abdurafikov R, Laitinen A, Juslin A, Mäkinen J, Ekelund E, Juhmen J, Saari M, Soinio T, Tukia SL. D3. 4 Interoperability of holistic energy systems in Espoo.
3. Watel-Dehaynin T. Moving towards a more sustainable model of energy production & consumption: a case for Indonesia. Massachusetts Institute of Technology; 2023.
4. Zangeneh P. *Knowledge representation and artificial intelligence for management of socio-technical risks in megaprojects* (Doctoral dissertation, University of Toronto (Canada)).
5. Jamiu OA, Chukwunweike J. DEVELOPING SCALABLE DATA PIPELINES FOR REAL-TIME ANOMALY DETECTION IN INDUSTRIAL IOT SENSOR NETWORKS. International Journal Of Engineering Technology Research and Management (IJETRM). 2023Dec21;07(12):497–513.
6. Makinen J. 5G Solutions: Opportunities and new business models for energy and mobility. Sparcs Project. 2023 Oct:1-47.
7. Solarin A, Chukwunweike J. Dynamic reliability-centered maintenance modeling integrating failure mode analysis and Bayesian decision theoretic approaches. *International Journal of Science and Research Archive*. 2023 Mar;8(1):136. doi:10.30574/ijsra.2023.8.1.0136.
8. Aleksia C, Bakhtiar AR. BRICS as new alternatives in reforming international financial institutions and economic partnerships. Insignia: Journal of International Relations. 2023 Nov 21;10(2):128-43.
9. AKINYELURE FM. Music and Dance Therapy; The Effectiveness of Occupational Therapy Intervention in Preventing Depression amongst Persons living with Alzheimer in Lagos Nigeria. Alzheimer's & Dementia. 2022 Dec;18:e069054.
10. Mohammadi N. Investigation of community energy business models from an institutional perspective: Intermediaries and policy instruments in selected cases of developing and developed countries. Sustainability. 2023 May 22;15(10):8423.
11. Oluwafemi I. Molecular surveillance frameworks advancing infection prevention practices within early childhood settings through environmental pathogen detection technologies. *Int J Mol Biol Biochem*. 2022;4(2):16-30. doi:10.33545/26646501.2022.v4.i2a.151.
12. George AS. Evaluating India's economic growth: challenges and opportunities on the path to 5 trillion dollars. Partners Universal International Innovation Journal. 2023 Dec 25;1(6):85-109.
13. Akinyelure FM, Adeyoola T, Adeife AA, Jet L. A study and training of careers on effective cognitive therapy for elderly to prevent dementia in Lagos, Nigeria.(Proposed

Project). Alzheimer's & Dementia. 2024 Dec;20:e092560.
14. Laboure M, Deffrennes N. Democratizing finance: The radical promise of fintech. Harvard University Press; 2022 Apr 5.
15. Chukwuebuka Festus Okoli, Joshua Olewu. Artificial intelligence and the future of inventorship: Comparative perspectives from the E.U. and emerging economies. Int J Comput Programming Database Manage 2024;5(2):81-86. DOI: 10.33545/27076636.2024.v5.i2a.171
16. Ozoegwu CG, Akpan PU. A review and appraisal of Nigeria's solar energy policy objectives and strategies against the backdrop of the renewable energy policy of the Economic Community of West African States. Renewable and sustainable energy reviews. 2021 Jun 1;143:110887.
17. Iyanuoluwa Oluwafemi. (2024). ENVIRONMENTAL MONITORING STRATEGIES INTEGRATING MOLECULAR DETECTION TECHNOLOGIES TO ENHANCE AGRICULTURAL BIOSECURITY AND SUSTAINABLE CROP PRODUCTION SYSTEMS. International Journal Of Engineering Technology Research & Management (IJETRM), 10(12), 757–772. https://doi.org/10.5281/zenodo.21152414
18. Hyun S. Current status and challenges of green digital finance in Korea. Green Digital Finance and Sustainable Development Goals. 2022 Jul 2:243-61.
19. Astesiano G, Lembo C, Morientes CS, Martínez PC, Suárez-Alemán A, Leduc D, Araújo AB, Hurtado J, Ojeda JL. PPP Americas 2023: Partnerships with Purpose.
20. Ogunsipe B. Building national data governance ecosystems: interoperable compliance frameworks for federally regulated industries. *Int J Res Publ Rev*. 2024 Dec;5(12):6208-6215. doi:10.55248/gengpi.07.0526.c1145.
21. Raj P, Vanga S, Chaudhary A. Cloud-Native Computing: How to design, develop, and secure microservices and event-driven applications. John Wiley & Sons; 2022 Oct 25.
22. Moro-Visconti R. Networking digital platforms and healthcare project finance bankability. Sustainability. 2021 Apr 30;13(9):5061.
23. Lu X. Accelerating private sector engagement in adaptation in Asia and the Pacific. ADB sustainable development working paper series; 2022 Nov 12.
24. Adebiyi MK. Artificial intelligence for resolving contract complexity and enhancing productivity in United States construction industry projects nationwide. Int J Comput Appl Technol Res. 2023;12(12):369-383. doi:10.7753/IJCATR1212.1032.
25. Tazhiyev A. Towards a Central Asia-as-a platform strategy and a digital solutions centre for sustainable development. Asia-Pacific Information Superhighway Working Paper Series. 2021(08).
26. Abdullahi BB. A spatial model identifying optimal locations for recyclable waste drop-off centers in New Haven County, Connecticut, USA. *Int J Chem Res Dev*. 2023;5(2):41-49. doi:10.33545/26646552.2023.v5.i2a.170.
27. Girón A, Ivanova A. Climate action, institutional investors, and just transition. Journal of Economic Issues. 2023 Apr 3;57(2):575-85.
28. Temitope Iyamu Fadairo. AI powered customer experience in financial services: Balancing personalization, efficiency, and regulatory compliance. Int J Finance Manage Econ 2023;6(2):237-247. DOI: 10.33545/26179210.2023.v6.i2.635
29. Akinleye OK, Adeyoyin O. Supplier Relationship Management Framework for Achieving Strategic Procurement Objectives. DOI: https://doi.org/10.32628/GISRRJ225430. 2022 Jul.
30. Oluwafemi I. Integrated PCR diagnostics and environmental monitoring for enhancing food security, soil health, and agricultural sustainability nationwide. *Int J Plant Pathol Microbiol*. 2021;1(2 Pt A):62-76.
31. Devidze N. Current state of green digital financing and the associated challenges. InGreen digital finance and sustainable development goals 2022 Jul 2 (pp. 29-50). Singapore: Springer Nature Singapore.
32. Dannouni A, Deutscher SA, Dezzaz G, Elman A, Gawel A, Hanna M, Hyland A, Kharij A, Maher H, Patterson D, Jones ER. Accelerating climate action with AI. Boston Consulting Group Special Report and Google. 2023 Nov.
33. Schindler S, Alami I, Jepson N. Goodbye Washington Confusion, hello Wall Street Consensus: contemporary state capitalism and the spatialisation of industrial strategy. New political economy. 2023 Mar 4;28(2):223-40.
34. Hassan K. Transforming health systems through scalable AI platforms: a roadmap for predictive, value-based care delivery. *Int J Eng Technol Res Manag*. 2024 Dec;8(12).
35. Adebowale OJ, Etukudoh EA. Market assessment and strategic roadmap for fuel cell technology in stationary power applications. Gyanshauryam Int Sci Refereed Res J. 2022 Sep;5(5):175-210.