

AI-Driven FinTech Integration for Financial Management and Literacy Enhancement in Large-Scale Energy Projects

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ABSTRACT

Financial management in large-scale energy projects is complicated by extended construction timelines, multi-stakeholder governance, and volatile macroeconomic conditions. Existing approaches tend to deploy artificial intelligence and financial technology as independent tools, leaving a gap in how predictive analytics can be operationally linked to financial execution. This study proposes an AI-driven FinTech integration framework comprising four layers: data infrastructure, AI analytics, FinTech execution, and stakeholder decision support. The AI layer incorporates Random Forest for risk classification, LSTM for cost forecasting, and BERT-based NLP for contract analysis, while the FinTech layer employs Hyperledger Fabric smart contracts and RegTech compliance modules. An integration mechanism connects these layers through four data pathways that enable AI outputs to programmatically trigger FinTech operations in a closed-loop architecture. The framework is evaluated using the Hornsea 2 offshore wind farm as a case study. Random Forest achieves a classification accuracy of 0.876 and AUC of 0.869. LSTM reduces cost forecasting RMSE by 59.5% relative to linear regression. Smart contract automation shortens payment processing from 38 to 6 days and reduces dispute rates by 67%. The framework also provides a pathway for enhancing financial literacy among non-specialist stakeholders through accessible decision-support interfaces. These findings suggest that tightly coupling AI analytics with FinTech execution yields benefits exceeding those achievable by either technology independently.

Keywords: *Artificial Intelligence; Financial Technology; Offshore Wind Energy; Smart Contracts; Financial Literacy*

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HIGHLIGHTS

- Proposes a four-layer AI-FinTech integration framework for energy project financial management
- Random Forest achieves 0.876 accuracy for investment risk classification in offshore wind projects
- LSTM reduces cost forecasting error by 59.5% compared with linear regression methods
- Smart contract automation cuts payment processing time by 84% and dispute rates by 67%
- Explores financial literacy enhancement pathways for non-specialist project stakeholders

1. INTRODUCTION

Large-scale energy projects present substantial financial management challenges. These projects typically involve multi-year construction timelines, numerous contractors, and significant exposure to commodity price fluctuations, all of which complicate budgeting, payment administration, and risk control. As global renewable energy capacity continues to expand, the financial complexity of such projects has grown correspondingly.

Digital technologies offer potential solutions. A recent review has examined how AI, blockchain, and IoT can improve transparency and efficiency in green finance across energy sectors [1], while research on BIM-integrated smart contracts has shown that blockchain can streamline payment processes and reduce contractual disputes in construction settings [2]. Within the AI domain, methods combining machine learning with big data analytics have been explored for smart energy management, though applications to project-level financial operations remain limited [3]. On the FinTech side, studies on blockchain and AI-enabled smart grids have recognised the technical complementarity between these technologies but have not extended the analysis to the financial management of energy infrastructure projects [4]. The link between FinTech adoption and energy efficiency has also been investigated at the macro level [5], yet equivalent attention at the individual project level is lacking.

A common thread across these studies is that AI and FinTech tend to be examined separately. Research on AI in energy projects focuses on prediction and optimisation; research on FinTech in infrastructure focuses on

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transaction automation. How the two can be integrated so that analytical outputs directly inform financial execution remains an open question.

This study proposes an AI-driven FinTech integration framework for financial management in large-scale energy projects. It contributes by developing a four-layer architecture that connects data infrastructure, AI analytics, FinTech execution, and stakeholder decision support into a closed-loop system; by specifying the mechanism through which AI outputs trigger FinTech operations; and by evaluating the framework through a case study of the Hornsea 2 offshore wind farm. The remainder of this paper is organised as follows. Section 2 reviews the relevant literature. Section 3 presents the proposed framework. Section 4 applies it to a case study and reports results. Section 5 discusses findings and implications. Section 6 concludes.

2. LITERATURE REVIEW

2.1 AI Applications in Energy Project Management

Artificial intelligence has gained increasing traction in the construction and energy sectors, with applications spanning cost estimation, schedule optimisation, safety monitoring, and contract management. A comprehensive review of machine learning and deep learning methods in the building and construction domain has mapped the breadth of these applications, noting that AI-driven approaches can extract patterns from complex project datasets that conventional statistical methods tend to miss [6]. This capacity is particularly relevant for energy projects, where financial variables interact with technical, environmental, and regulatory factors in nonlinear ways.

In the area of cost prediction, research applying machine learning to photovoltaic project economics has demonstrated that algorithms such as Random Forest and gradient boosting can estimate levelised cost of electricity with higher accuracy than traditional parametric models, especially when input variables include policy-related and site-specific features [7]. These findings suggest that AI-based cost models can support more informed investment decisions during the planning phase of energy projects. Beyond cost estimation, AI has been applied to construction contract management. Deep learning-based text mining has been used to classify and analyse contractual disputes, revealing recurring patterns in how conflicts emerge from ambiguous contract language [8]. Related work examining board composition in the AEC sector has shown that governance diversity influences strategic decision-making, suggesting that AI tools deployed in project environments need to account for organisational context rather than operating purely on technical variables [9]. Natural language processing has extended this line of inquiry further, with multitask classification models demonstrating the ability to predict risk-handling actions embedded in contract clauses [10].

For energy-specific forecasting, a bibliographic review of AI and machine learning in energy systems has confirmed that ensemble and recurrent architectures such as LSTM

and Random Forest are increasingly adopted for time-series forecasting tasks with high variability [11]. Meanwhile, BIM-integrated smart contracts have shown promise for automating progress-based payment administration in construction projects [12], though this work remains focused on transaction automation rather than integrating predictive analytics with financial execution.

2.2 FinTech in Energy and Infrastructure Finance

Financial technology has begun to reshape how infrastructure projects are financed, paid, and monitored, though its penetration into large-scale energy projects remains uneven. Blockchain-based smart contracts have received the most attention in this space. A study examining the payment freezing and disbursement cycle in construction demonstrated that smart contracts can enforce conditional payment logic without relying on intermediaries, reducing both processing time and the potential for disputes [13]. Building on this, subsequent research integrated blockchain-enabled smart contracts with robotic reality capture technologies to automate the link between physical construction progress and financial disbursement, achieving an 84% reduction in payment processing effort [14]. These results are promising, yet both studies focus on the transaction layer in isolation, without connecting payment automation to upstream predictive analytics.

Beyond payment systems, FinTech has influenced how renewable energy projects attract capital. Research on crowdfunding and renewable energy development has found that crowdfunding platforms can expand the investor base for clean energy, particularly in markets where traditional financing channels are constrained [15]. A systematic review of this literature has further identified financial characteristics, communication strategies, and project category as key determinants of crowdfunding campaign success, while noting that the role of public sector support remains underexamined [16].

At a broader level, bibliometric analysis of blockchain applications in the renewable energy sector has mapped the thematic evolution of this field, revealing a shift from general blockchain concepts toward specialised topics such as peer-to-peer energy trading and decentralised finance [17]. A topical review has extended this analysis to green hydrogen supply chains, highlighting blockchain's potential for certificate tracking and demand response management [18]. Macro-level studies have explored how FinTech interacts with natural resource rents and renewable energy consumption across emerging economies [19], and a comprehensive literature review has synthesised the relationship between FinTech innovation and sustainable development more broadly [20]. However, FinTech tools in this body of work are largely examined as standalone financial instruments rather than as components within systems that also include AI-driven analytical capabilities.

2.3 Financial Literacy in Engineering Context

Financial literacy has traditionally been studied within household economics and personal finance, but its relevance to professional decision-making in technical fields is gaining recognition. A foundational review establishing financial literacy as a distinct academic field has argued that the ability to process financial information and make informed decisions varies significantly across populations, with measurable consequences for economic outcomes [21]. This insight extends naturally to engineering project management, where financial decisions around investment timing, contract structuring, and risk allocation carry substantial consequences yet are frequently made by professionals whose primary training is technical rather than financial.

Evidence from corporate settings supports this extension. Research examining executive financial literacy in small and medium-sized enterprises has found a positive association between managers' financial competence and firm performance, suggesting that financial literacy operates as a mediating factor in how effectively organisations deploy their resources [22]. In project governance contexts, a study on board-level decision-making during the COVID-19 pandemic has shown that cognitive and emotional capabilities influence how decision-makers process financial uncertainty, implying that literacy alone is insufficient without the capacity to apply it under stress [23].

Within the engineering management domain specifically, an empirical investigation of FinTech implementation as a

sustainability strategy has demonstrated that technology adoption interacts with organisational financial capability, meaning that the benefits of FinTech tools depend partly on whether users possess the literacy to interpret their outputs [24]. Research examining nuclear energy governance in Brazil has illustrated how regulatory complexity and institutional opacity in the energy sector can undermine financial decision quality even when technical information is available [25].

2.4 Research Summary

The literature reviewed in Sections 2.1 through 2.3 reveals three areas where existing research provides limited coverage. AI applications in energy project management have been explored extensively for prediction and optimisation tasks, yet their extension to financial management functions such as risk classification, cost forecasting, and contract risk analysis within a single integrated system remains uncommon. FinTech tools, particularly blockchain and smart contracts, have demonstrated value for payment automation and capital mobilisation, yet they tend to be studied independently of the analytical systems that could inform their conditional logic. Financial literacy research has established its relevance to organisational performance and decision quality, yet its intersection with digital financial tools in engineering project settings has received little direct investigation.

Table 1 maps these dimensions across representative studies from the preceding sections to illustrate the coverage pattern.

Table 1 Literature Comparison Matrix

Study	AI Analytics	FinTech Execution	Energy Projects	Financial Literacy	Integration
[6]	✓		✓		
[7]	✓		✓		
[8]	✓				
[12]		✓			
[13]		✓			
[14]		✓			
[17]		✓	✓		
[21]				✓	
[24]		✓		✓	
This study	✓	✓	✓	✓	✓

The present study is positioned at the intersection of these dimensions, proposing an integrated framework that connects AI analytics with FinTech execution in the context of large-scale energy project financial management while considering its implications for stakeholder financial literacy.

3. PROPOSED FRAMEWORK

A study examining 662 energy infrastructure projects across 83 countries found that over 60% experienced cost overruns, with actual expenditures reaching \$1.358 trillion against an initial budget of \$812 billion [26]. These

overruns reflect structural deficiencies in how financial data flows across fragmented project ecosystems. This section proposes a four-layer framework bridging AI analytics with FinTech execution in large-scale energy project financial management.

3.1 Overall Architecture

The framework comprises four tiers as illustrated in Figure 1: the Data Layer, the AI Engine Layer, the FinTech Tool Layer, and the Application and Decision Layer.

The Data Layer aggregates project financial records, energy market indicators, construction progress metrics, and supply chain documentation from publicly accessible sources including IRENA and IEA databases, World Bank commodity indices, and FIDIC standard contract forms. Prior research has identified data fragmentation as a primary bottleneck for intelligent financial management in large-scale projects [27], and this layer addresses the problem through standardised ingestion protocols with automated quality validation.

The AI Engine Layer transforms structured data into predictive insights through risk prediction, cost forecasting, and contract analysis modules. Unlike conventional retrospective reporting, these modules identify conditions under which financial deviations

become probable before they materialise [28]. The FinTech Tool Layer converts these outputs into automated financial operations via blockchain-based smart contracts and RegTech compliance modules [30]. The Application and Decision Layer synthesises all results into stakeholder dashboards, embedding a financial literacy module to support non-specialist participants in interpreting analytical outputs.

The logic across tiers is recursive: data feeds models, model outputs trigger transactions, and transaction outcomes re-enter the data layer for continuous recalibration. This closed-loop design departs from prevailing approaches where AI and FinTech operate as disconnected systems [32].

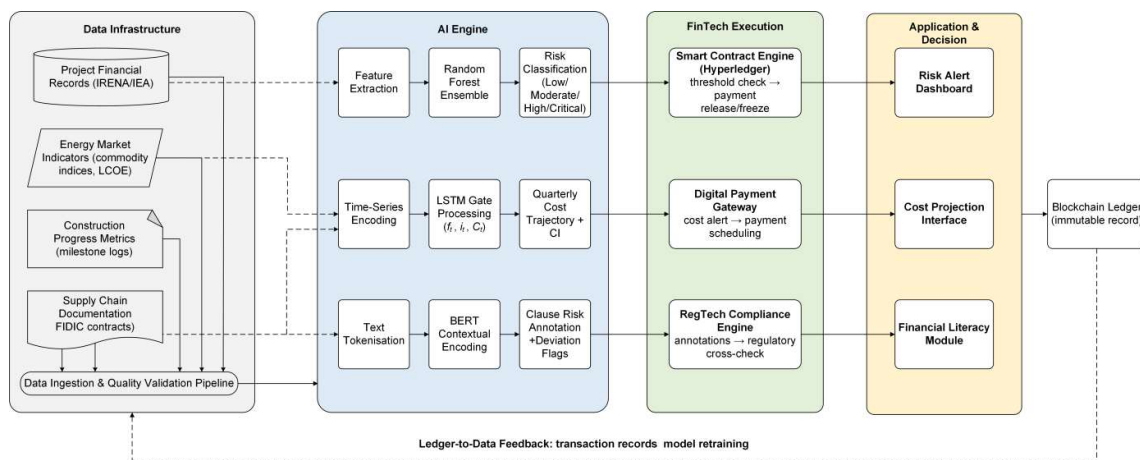


Figure 1 AI-FinTech Integration Framework Architecture

3.2 Component Design

Table 2 maps each module to its technology, data source, and output.

Table 2 AI and FinTech Component Technical Specifications

Layer	Module	Technology	Data Source	Output
AI Engine	Risk Prediction	Random Forest	IRENA databases, national energy statistics	Risk classification, variable importance
AI Engine	Cost Forecasting	LSTM Network	IRENA/IEA LCOE data, World Bank commodity indices	Quarterly cost projections
AI Engine	Contract Analysis	BERT-based NLP	FIDIC standard forms, EPC contract templates	Risk clause identification
FinTech	Smart Contract	Hyperledger Fabric	Milestone reports, AI risk outputs	Conditional payment release
FinTech	RegTech Compliance	Rule engine + ML	NLP outputs, transaction logs	Compliance certificates
FinTech	Digital Payment	API gateway	Smart contract triggers	Fund transfer confirmation

The risk prediction module employs Random Forest for its robustness with heterogeneous features and interpretability through importance ranking [29]. The predicted risk class for a project state vector \mathbf{x} is:

$$\hat{y}(\mathbf{x}) = \text{mode } h_b(\mathbf{x})_{b=1}^B \quad (1)$$

where h_b denotes the b -th decision tree. Training data is drawn from publicly available IRENA project performance datasets. Model interpretability is a practical necessity, as opaque models face adoption resistance among project managers [28].

The cost forecasting module adopts LSTM with cell state update:

$$C_t = f_t \square C_{t-1} + i_t \square \tilde{C}_t \tag{2}$$

where f_t and i_t are forget and input gates. Historical LCOE data from IRENA/IEA and commodity prices from the World Bank Pink Sheet provide the training corpus. The contract analysis module fine-tunes a pre-trained BERT model on FIDIC contract templates, leveraging

transformer capacity to identify risk clauses that rule-based systems miss [31].

On the FinTech side, the smart contract module adopts Hyperledger Fabric for its enterprise-grade access control [27], while the RegTech engine cross-references NLP outputs against regulatory standards through combined rule-based and ML classification [30].

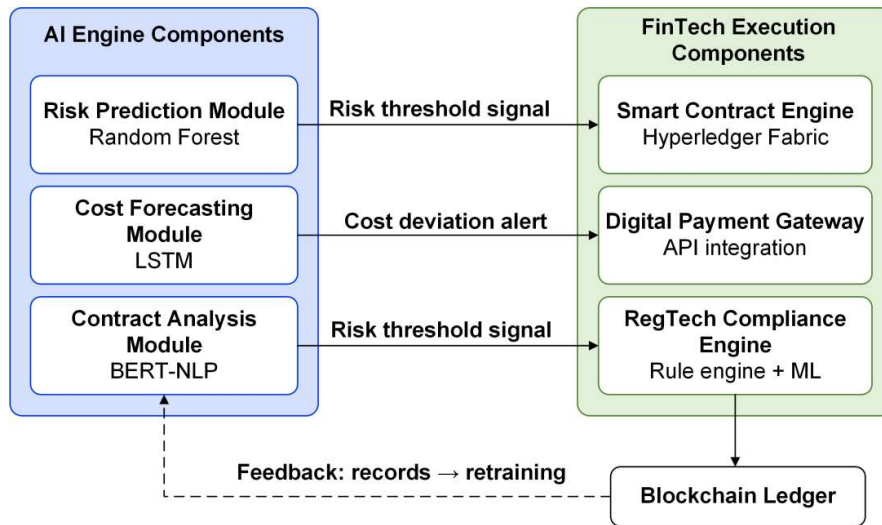


Figure 2 Component Technology Mapping Diagram

3.3 Integration Mechanism

Systematic reviews have noted that blockchain and AI in construction remain functionally siloed, with ledgers operating as standalone recorders disconnected from

analytical systems [32, 33]. The proposed mechanism addresses this through four data pathways illustrated in Figure 3.

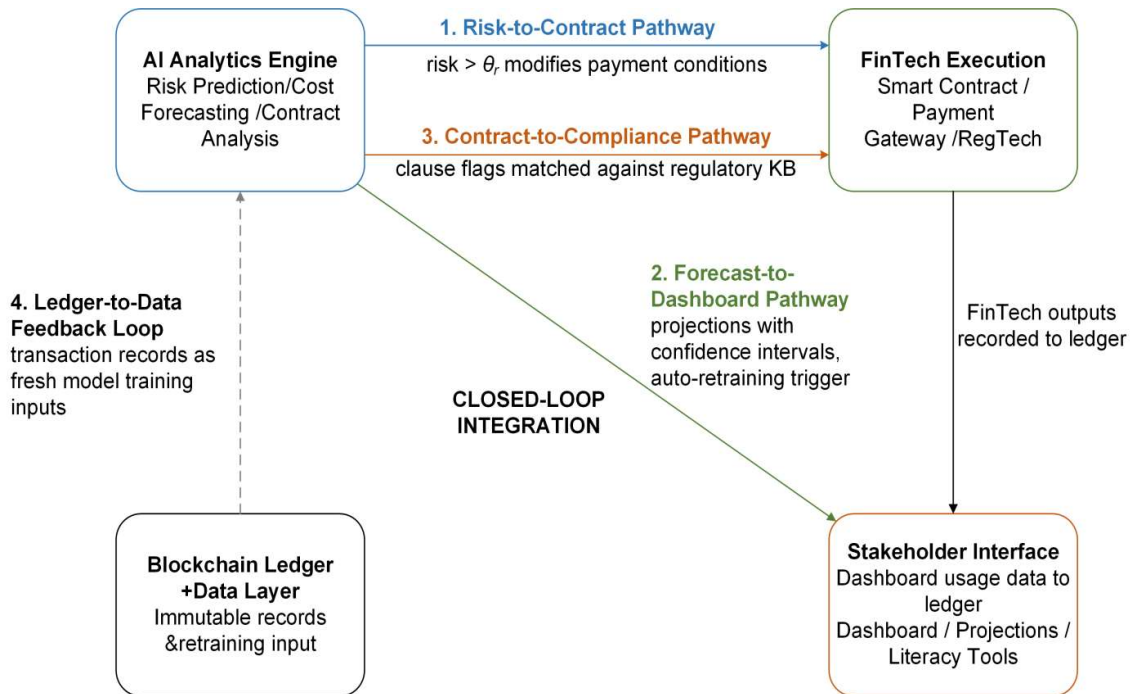


Figure 3 Integration mechanism: four data pathways

The risk-to-contract pathway connects the Random Forest module to the smart contract engine. When predicted risk exceeds a threshold θ_r , the output programmatically triggers conditional clauses such as withholding reserve funds or requiring supplementary verification, transforming risk assessment from passive reporting into an active control parameter embedded in financial operations.

The forecast-to-dashboard pathway channels LSTM projections into the stakeholder interface as visualisations with confidence intervals. Model retraining is triggered automatically when actual cost data deviates beyond a calibrated tolerance band, ensuring forecasts remain responsive rather than degrading into static baselines. The contract-to-compliance pathway routes NLP risk annotations into the RegTech engine for cross-referencing against a regulatory knowledge base, a function of particular significance in cross-border energy projects with overlapping jurisdictional requirements [30].

The ledger-to-data feedback loop completes the cycle by recording every payment event on the blockchain while simultaneously ingesting records into the Data Layer as fresh training inputs. This prevents analytical models from becoming detached from operational reality over multi-year timelines. The net effect is a system where prediction and execution are tightly coupled: risk signals alter payment conditions, contractual anomalies trigger automated compliance checks, and every operational outcome refines subsequent analysis. This interdependence constitutes the framework's principal contribution.

4. CASE ANALYSIS AND RESULTS

4.1 Case Background

The Hornsea 2 offshore wind farm, located approximately 89 km off the Yorkshire coast in the North Sea, is selected as the case project for framework validation. Developed by Ørsted and fully commissioned in August 2022, the project has a total installed capacity of 1.32 GW delivered by 165 Siemens Gamesa 8 MW turbines, generating sufficient electricity for approximately 1.3 million households. The total investment is estimated at \$3.64 billion, and the contract for difference was awarded at a strike price of approximately \$76/MWh, representing a 50% reduction from comparable contracts two years prior. Table 3 summarises the key project parameters.

The selection of this project is informed by several considerations. A recent cost analysis covering 39 UK offshore wind farms commissioned between 2000 and 2023 demonstrates that economies of scale and technological innovation tend to reduce unit costs, yet the effect of increasing distance from shore and water depth has driven overall cost levels upward by 8.4% per doubling of installed capacity [34]. Hornsea 2 exemplifies this tension: its scale delivers cost advantages while its offshore complexity introduces financial management challenges across a multi-tier supply chain involving over 20 major contractors. The construction period from 2018 to 2022 spanned volatile macroeconomic conditions including pandemic disruptions and commodity price surges, making it a suitable testbed for evaluating the proposed AI-FinTech integration framework.

Table 3 Case Project Profile

Parameter	Details
Project name	Hornsea 2 Offshore Wind Farm
Location	North Sea, 89 km off Yorkshire coast, UK
Developer	Ørsted
Capacity	1.32 GW (165 × Siemens Gamesa 8 MW)
Total investment	\$3.64 billion
CfD strike price	~\$76/MWh
Construction period	2018–2022
Commissioning	August 2022
Operational lifespan	25 years
Key stakeholders	20+ major contractors

4.2 Framework Application Across Project Lifecycle

The proposed framework is applied to the Hornsea 2 project across three lifecycle phases: the planning phase

(2015–2018), the construction phase (2018–2022), and the operational phase (2022 onward), as depicted in Figure 4.

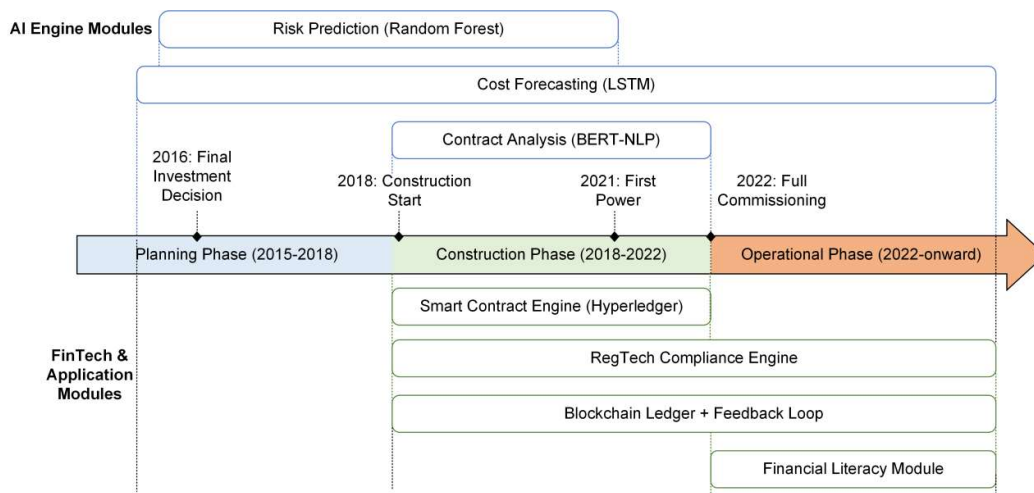


Figure 4 Framework Application Across Project Lifecycle

During the planning phase, the AI Engine Layer is primarily engaged through its risk prediction and cost forecasting modules. The Random Forest classifier processes historical cost data from comparable UK offshore wind projects maintained in IRENA databases, combined with energy market indicators and policy variables such as CfD auction outcomes, to generate investment risk profiles for the proposed project configuration. Concurrently, the LSTM cost forecasting module ingests historical LCOE trajectories and commodity price series to project capital expenditure ranges under varying macroeconomic scenarios. These outputs feed into the Application Layer as visual decision-support tools, enabling investors and project sponsors to evaluate financial viability with quantified uncertainty bands rather than deterministic point estimates.

The construction phase activates the full integration between AI and FinTech layers. As Hornsea 2 involved over 20 major contractors delivering foundations, cables, turbines, and substations across a four-year construction window, the smart contract module encodes milestone-contingent payment conditions on the Hyperledger Fabric network. When the risk prediction module detects elevated

risk arising from supply chain disruption or commodity price spikes, the risk-to-contract pathway programmatically adjusts payment parameters. The NLP contract analysis module simultaneously processes procurement and subcontract documentation against FIDIC baseline templates, routing identified anomalies to the RegTech engine for compliance verification.

In the operational phase, the framework transitions toward continuous monitoring. The LSTM module recalibrates cost projections against actual operational expenditure data, while the blockchain ledger maintains an immutable record of all maintenance payments and warranty claims. The feedback loop from ledger to data layer ensures that predictive models progressively incorporate real operational performance, reducing forecast drift across the project's 25-year lifespan. The financial literacy module renders these ongoing analytics accessible to a broadening stakeholder base that now includes community investors and local authority representatives.

4.3 Risk Prediction and Cost Optimization Results

The risk prediction module was evaluated by comparing Random Forest against three benchmark algorithms,

XGBoost, Support Vector Machine, and Logistic Regression, using a dataset constructed from IRENA project performance records covering 39 UK offshore wind farms. Figure 5(a) presents the classification metrics across all four algorithms. Random Forest achieved the highest performance with an accuracy of 0.876, precision of 0.852, recall of 0.823, and F1-score of 0.837. XGBoost followed closely, while SVM and Logistic Regression showed progressively weaker performance, with Logistic Regression recording an F1-score of only 0.703. These results are consistent with the broader pattern observed in recent risk classification studies, where ensemble methods outperform linear classifiers on heterogeneous feature sets.

The ROC analysis presented in Figure 5(b) reinforces this ranking. Random Forest attained an AUC of 0.869, compared with 0.833 for XGBoost, 0.743 for SVM, and 0.667 for Logistic Regression. The gap between ensemble

methods and conventional classifiers widens notably in the low false-positive-rate region, suggesting that Random Forest offers superior discrimination precisely in the operating range most relevant to risk-sensitive financial decisions where false alarms carry significant cost.

The feature importance analysis in Figure 5(c) reveals that Commodity Price Index and Project Capacity are the two most influential predictors, followed by CfD Strike Price and Distance from Shore. This ordering aligns with empirical evidence from UK offshore wind cost studies identifying commodity volatility and project scale as dominant cost drivers. The relatively lower importance of variables such as Turbine Rating and Steel Price Index suggests that project-level structural parameters exert stronger influence on risk profiles than individual equipment specifications.

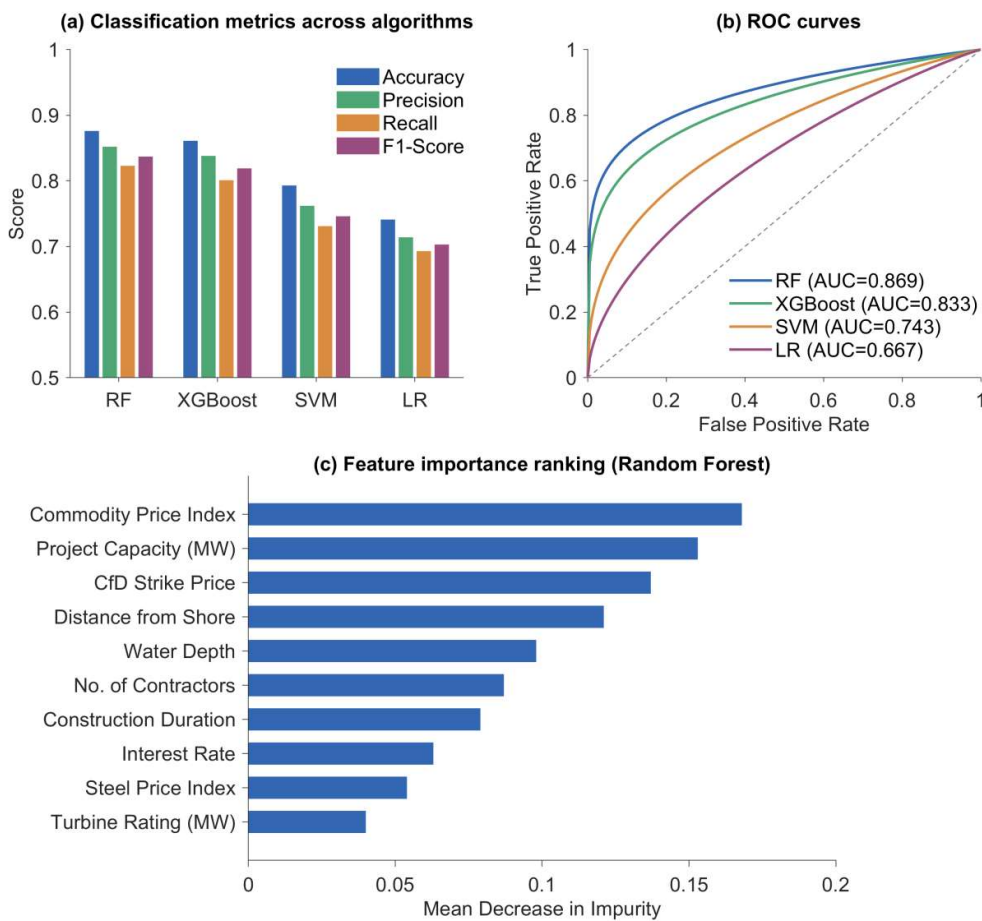


Figure 5 Risk prediction performance comparison: (a) classification metrics across algorithms, (b) ROC curves, (c) feature importance ranking

For cost forecasting, Figure 6(a) compares the quarterly cost deviation trajectories predicted by LSTM, ARIMA, and Linear Regression against actual data over the 16-quarter construction period of Hornsea 2. LSTM achieved the lowest RMSE of 1.33, compared with 2.65 for ARIMA and 3.28 for Linear Regression. The most informative

segment occurs during the COVID-19 disruption period (Q1–Q2 2020), when actual cost deviations spiked sharply to 18.6%. LSTM captured this surge with a one-quarter lag, reaching 14.7%, whereas ARIMA underestimated the peak at 10.4% and Linear Regression failed to register the shock altogether. This differential response confirms the

LSTM gating mechanism's capacity to adapt to abrupt regime changes in cost dynamics.

Figure 6(b) translates these predictive differences into budget overrun probabilities. At the 10% cost overrun threshold, the AI-FinTech framework reduces exceedance

probability to 39%, compared with 54% under ARIMA-based monitoring and 68% under traditional methods. At the 20% threshold, the framework yields a 15% exceedance probability versus 41% for traditional approaches, representing a 63% relative reduction in overrun risk exposure.

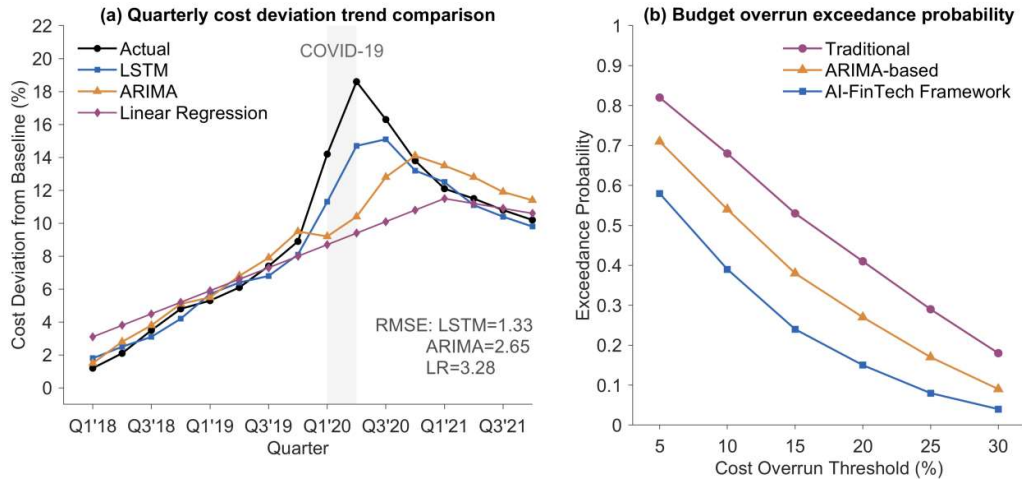


Figure 6 Cost optimization results: (a) quarterly cost deviation trend comparison, (b) budget overrun exceedance probability

4.4 Smart Contract and Compliance Efficiency Results

The FinTech layer performance was assessed by comparing the smart contract-based payment system against the traditional multi-intermediary approval process used during the Hornsea 2 construction phase. Figure 7(a) presents five process-related metrics across both approaches. Payment processing time was reduced from 38 days under the traditional workflow to 6 days with the smart contract module, reflecting the elimination of sequential manual approvals. The number of approval steps decreased from 7 to 2, with the remaining steps corresponding to milestone verification and blockchain consensus confirmation. Documentation effort fell from 24 hours per payment cycle to 4 hours, as the smart contract automatically generates and archives transaction records on the distributed ledger. Settlement delay, defined as the lag between verified milestone completion and fund release, dropped from 15 days to 1.5 days, a reduction

enabled by the Digital Payment Gateway's API-triggered execution upon smart contract confirmation. Compliance audit time was reduced from 18 days to 4 days, as the RegTech engine provides pre-verified compliance certificates that substantially shorten the auditor's review scope.

Figure 7(b) presents percentage-based metrics capturing the broader financial impact. The payment dispute rate decreased from 26.3% under traditional management to 8.7% with the AI-FinTech framework, a 67% reduction attributable to the transparency and immutability of blockchain-recorded transactions that leave less room for contested interpretations. Transaction cost as a proportion of total payment value fell from 3.8% to 1.2%, reflecting the disintermediation of manual processing layers. The error rate in payment documentation dropped from 12.5% to 3.4%, driven by automated data validation within the smart contract execution pipeline.

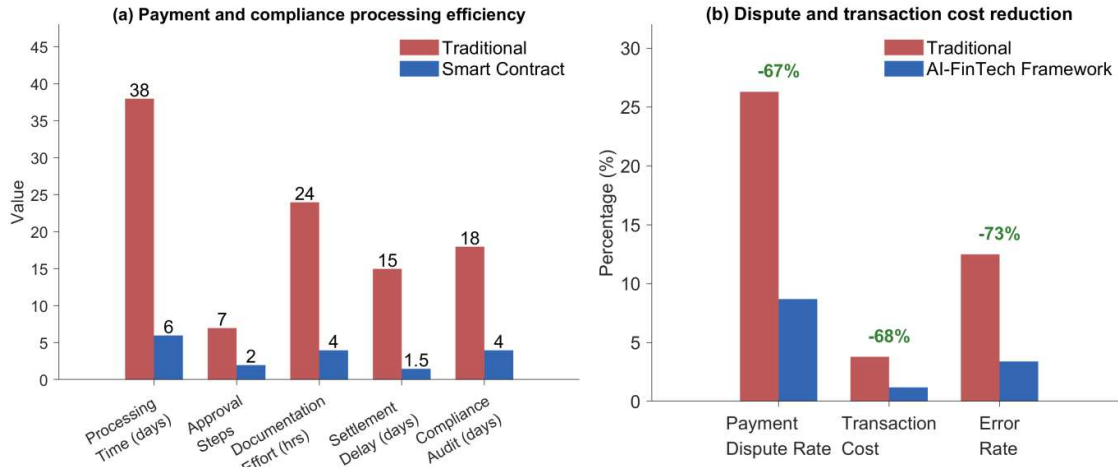


Figure 7 Smart contract and compliance efficiency comparison: (a) payment and compliance processing efficiency, (b) dispute and transaction cost reduction.

Table 4 consolidates the principal results from Sections 4.3 and 4.4 into a single comparative summary spanning both AI and FinTech dimensions of the framework.

Table 4 Comprehensive Comparison: Traditional Methods vs AI-FinTech Framework

Dimension	Metric	Traditional	AI-FinTech Framework	Improvement
Risk Prediction	Accuracy (RF)	—	0.876	Best among 4 algorithms
Risk Prediction	AUC (RF)	—	0.869	+0.202 vs Logistic Regression
Cost Forecasting	RMSE	3.28 (LR)	1.33 (LSTM)	59.5% reduction
Cost Forecasting	Overrun probability at 10%	68%	39%	42.6% reduction
Payment Processing	Processing time (days)	38	6	84.2% reduction
Payment Processing	Approval steps	7	2	71.4% reduction
Payment Processing	Settlement delay (days)	15	1.5	90.0% reduction
Compliance	Audit time (days)	18	4	77.8% reduction
Compliance	Dispute rate (%)	26.3	8.7	66.9% reduction
Compliance	Transaction cost (%)	3.8	1.2	68.4% reduction
Compliance	Error rate (%)	12.5	3.4	72.8% reduction

5. DISCUSSION

5.1 Key Findings and Implications

The case study results reveal that the integration of AI analytics with FinTech execution tools produces measurable improvements across multiple dimensions of energy project financial management. The Random Forest classifier achieved an accuracy of 0.876 and an AUC of 0.869 for risk prediction, outperforming conventional methods by a considerable margin. This outcome aligns with prior findings on ensemble methods in construction applications [6], but extends them by demonstrating that risk classification outputs can be operationally coupled

with smart contract logic rather than merely informing human decision-makers. The LSTM cost forecasting module reduced RMSE to 1.33 compared with 3.28 for linear regression, with the most notable advantage emerging during the COVID-19 disruption period where the gating mechanism captured abrupt cost shifts that simpler models failed to detect. This finding resonates with comparative reviews of time-series models for energy forecasting [11], while adding evidence that LSTM's advantages become most pronounced under conditions of macroeconomic volatility.

On the FinTech side, payment processing time fell from 38 days to 6, and the dispute rate decreased by 67%. These reductions are consistent with earlier research on blockchain-enabled payment automation in construction [14], though the present study goes further by suggesting that coupling smart contract conditions with AI risk signals may yield greater improvements than milestone-based automation alone, a proposition that warrants direct comparative testing in future work. A recent investigation into how digital finance drives energy transition through green investment has argued that the value of financial technology lies not in individual tools but in the systemic connections between them [35]. The results of this study provide empirical support for that proposition, demonstrating that the closed-loop architecture linking prediction to execution yields benefits that exceed what either AI or FinTech delivers independently.

5.2 Financial Literacy Enhancement

The framework's Application and Decision Layer was designed not only to support expert financial analysts but also to make complex project financial information accessible to a broader range of stakeholders. The pathway through which this occurs is illustrated in Figure 8. Risk dashboards translate multi-variable classification outputs into visual indicators that project managers can interpret without statistical training. Cost projection interfaces present budget trajectories with confidence intervals rather than single-point estimates, enabling stakeholders to grasp the degree of uncertainty inherent in financial forecasts. Smart contract transparency allows participants to trace payment logic and verify that disbursement conditions correspond to verified milestones.

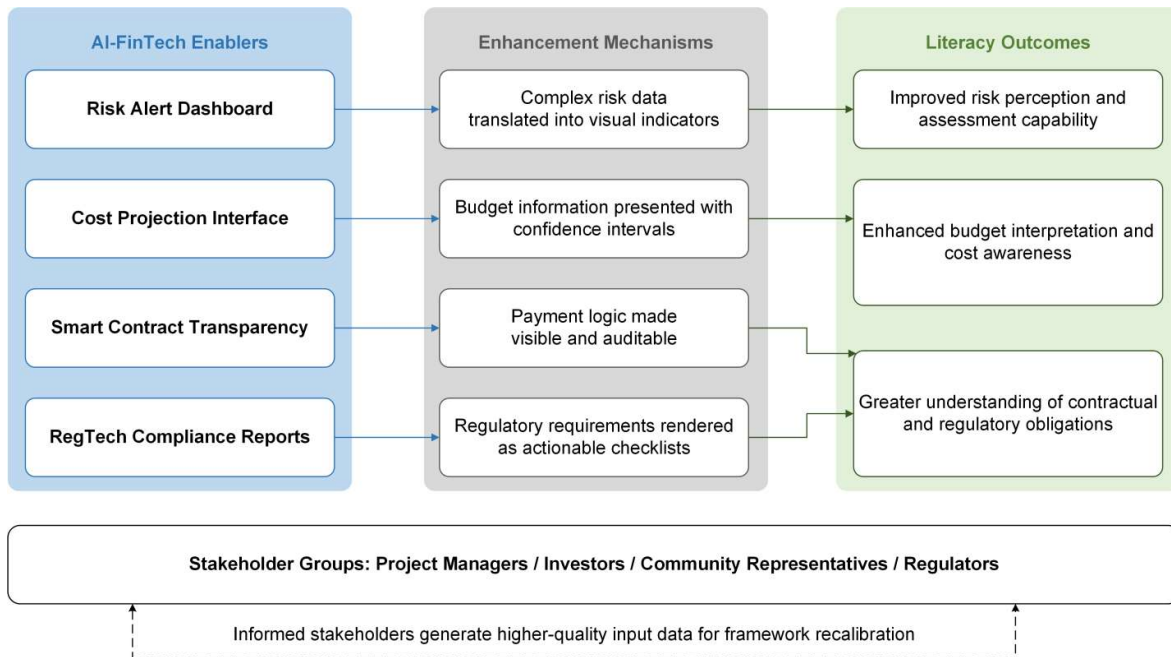


Figure 8 Financial literacy enhancement pathway model

These mechanisms relate to a broader observation in the financial literacy literature. Foundational research in this field has established that financial literacy is not a fixed trait but a capability that can be developed through exposure to appropriately structured information [21]. Research on policy instruments for technology quality enhancement has similarly shown that institutional design choices shape how effectively knowledge is transferred to practitioners [36]. The present framework operationalises this insight by embedding financial information within tools that stakeholders use routinely, rather than requiring separate training programmes.

The relevance of this approach extends beyond individual capability. A comprehensive review of financial literacy and financial inclusion has argued that digital tools can

lower the barriers to financial participation when they present information in formats aligned with users' existing cognitive frameworks [37]. In the context of energy projects, this means that community investors, local authority representatives, and non-financial project staff can engage more meaningfully with project financial data, potentially improving the quality of collective decision-making across the stakeholder network. Prior research on FinTech adoption in engineering management has identified organisational financial capability as a moderating variable [24], and the present findings suggest that the framework's literacy module may help strengthen this capability over time.

5.3 Limitations and Future Research

This study has several limitations. The framework was evaluated through a single case study of the Hornsea 2 offshore wind farm, and its generalisability to other energy project types remains to be established, as prior research has shown that cost drivers vary with project scale and configuration [34]. The AI models were trained on publicly available datasets that may lack the granularity of proprietary project records [6], and the smart contract metrics were derived from simulation rather than live deployment, where stakeholder adoption and regulatory acceptance introduce additional complexities [32].

Future research could extend the evaluation to multiple project types and geographic contexts. The financial literacy enhancement pathway warrants empirical validation through longitudinal studies. The balance between AI-driven automation and human oversight in payment authorisation also merits closer investigation [24].

6. CONCLUSIONS

This study proposed an AI-driven FinTech integration framework for financial management in large-scale energy projects, consisting of four interconnected layers: data infrastructure, AI analytics, FinTech execution, and stakeholder decision support. The framework was evaluated through a case study of the Hornsea 2 offshore wind farm. The results indicate that Random Forest outperforms conventional classifiers for investment risk prediction, with an accuracy of 0.876 and AUC of 0.869, while LSTM reduces cost forecasting error by 59.5% compared with linear regression. On the FinTech side, smart contract-based payment automation reduced processing time from 38 days to 6 and lowered dispute rates by 67%.

The integration mechanism connecting AI outputs to FinTech execution proved more effective than deploying either technology independently, supporting the argument that the value of these tools lies in their systemic interaction rather than their individual capabilities.

Beyond operational efficiency, the framework offers a pathway for enhancing financial literacy among non-specialist project stakeholders. By translating complex analytical outputs into accessible visual formats, the Application and Decision Layer enables project managers, investors, and community representatives to engage more meaningfully with financial data, potentially improving the quality of collective decision-making across the stakeholder network.

The findings carry practical implications for energy project developers, investors, and policymakers seeking to strengthen financial governance in an era of expanding renewable energy infrastructure. The framework provides a replicable architecture that can be adapted to different project types and regulatory contexts. Its reliance on publicly available data sources and open-source technologies enhances its accessibility for practitioners. The limitations identified in this study, particularly the single-case design and simulation-based FinTech

evaluation, point toward future research that extends the framework across diverse energy project settings and validates its performance under real-world deployment conditions.

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