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Article

AI-enhanced strategic management of foreign direct investment in China: decoding the mediating effects of labor productivity and infrastructure development on economic growth

Zhibin Jia, Oyyappan Duraipandi*

School of Business and Management, Lincoln University College, 47301 Petaling Jaya, Selangor Darul Ehsan, Malaysia

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*Corresponding author
Email address:
oyyappan@lincoln.edu.my

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ABSTRACT

The integration of artificial intelligence into foreign direct investment management represents a paradigm shift in strategic decision-making, particularly as traditional analytical frameworks prove inadequate for navigating complex economic environments characterized by volatility, uncertainty, complexity, and ambiguity. This study develops an AI-enhanced strategic management framework for optimizing foreign direct investment (FDI) allocation decisions while examining the mediating roles of labor productivity and infrastructure development in facilitating economic growth outcomes in China's digital transformation context. Employing a mixed-methods approach combining panel data analysis from 30 Chinese provinces (2010-2023) with machine learning algorithms including Random Forest, Support Vector Machines, and Neural Networks, the research integrates traditional econometric techniques with AI-powered predictive modeling to capture complex non-linear relationships. AI-enhanced management achieves 21% higher prediction accuracy (R^2=0.743) compared to traditional methods (R^2=0.614) while reducing processing time by 78%. Labor productivity mediates 41.2% and infrastructure development 21.0% of the total effect on economic growth, with significant synergistic interactions (β=0.087, p<0.01) amplifying individual contributions. The findings establish AI integration as essential for modern FDI management, providing theoretical advancement through the four-layer architectural framework and practical implementation guidelines. The research demonstrates that successful AI-enhanced FDI strategies require simultaneous optimization of technological capabilities, human capital development, and infrastructure readiness.

1. Introduction

The modern digital transformation era has revolutionized strategic management models in global economies, with artificial intelligence becoming the key driver for organizational transformation and value creation [1]. Under this dynamic technology platform, foreign direct investment (FDI) management has been changed more than ever before due to the nature of the complexity of the decision-making within the framework of the 4.0 industrial revolution and the readiness of artificial intelligence to cope with an environment of complexity, volatility, uncertainty, and ambiguity [2]. Indeed, the very fact that China holds the status of being the second world power and a major draw for FDI, with a share of 12.3 percent in the international cross-border DI, despite its ups and downs in flow entry and outflow history, demonstrates the absolute need for new comprehensive analytical schemata to generate efficiency in investment allocation – ones that can make smart use of new technologies. The combination of the digital economy, large infrastructure programmes, and strategic focus on technology, which is unique to empirical conditions in China, will be used as an empirical pattern to explore whether and how AI applications can be used to supplement traditional FDI management practices when confronted with the multi-faceted challenges of economic development in developing economies. Conventional FDI management theories and models, although historically appropriate, present several limitations for addressing the dynamic complexity of a modern economy where multiple factors act simultaneously at temporal and geographic scales. The core research problem addressed in this study is: How can artificial intelligence technologies be systematically integrated into foreign direct investment management frameworks to overcome the limitations of traditional analytical approaches, and what are the mechanisms through which AI-enhanced FDI influences economic growth in the context of China's digital transformation? Traditional methods frequently require static analytical models that are difficult to adapt to real-time market dynamics, unable to process large amounts of heterogeneous data sources, and incapable of capturing complex non-linear economic relationships, while the rapid evolution of AI technologies offers unprecedented opportunities for enhancing investment decision-making that remain theoretically underexplored and empirically unvalidated [3]. Recent empirical findings suggest that digital transformation ventures have an effect on FDI flows and distribution flows, digitalization being positively associated with the attractiveness toward foreign investment being attracted to low-income economies, and their infrastructure novelty constitutes a tool for development [4]. Increasing awareness that digital transformation stimulates productivity gains via a series of mediating forces that comprise better innovation capacity and efficient allocation of resources, therefore underscores the importance of mainstream AI as part of strategic FDI management processes [5].

This study bridges theoretical and practical gaps in the literature by pursuing the following specific research objectives: (1) To develop and validate an AI-enhanced strategic management framework that integrates machine learning algorithms with traditional FDI theories for optimizing investment allocation decisions; (2) To empirically examine the mediating roles of labor productivity and infrastructure development in the relationship between AI-enhanced FDI and economic growth using panel data from 30 Chinese provinces (2010-2023); (3) To quantify the performance improvements of AI-enhanced approaches compared to traditional FDI management methods through comprehensive comparative analysis; (4) To investigate regional heterogeneity in AI-FDI effectiveness across different provincial contexts (coastal vs. inland, high-tech vs. traditional); and (5) To provide actionable policy recommendations through simulation-based scenario analysis for optimizing AI readiness and FDI attraction strategies.

The proposed model has theoretical contributions to the extant IBD literature by adding two innovative conceptual extensions to the current IBD theories that include artificial intelligence capabilities in those theories, thereby enriching our understanding of the role played by technology in the strategy-making process [6]. The findings also offer valuable practical implications for multinational companies, public bodies, and policymakers to explore the role of a technology-driven strategy based on AI to enhance the efficiency of investment decision-making processes, taking into consideration the maximization of the effects on economic development. The policy implications are not limited to China, offering valuable insights for other emerging economies adopting similar digital transformation strategies to enhance their FDI attraction policies through technological innovation and infrastructure development.

2. Literature review and theoretical framework

The transition from traditional decision-making models to AI-supported strategic management represents a paradigmatic shift in addressing complex investment optimization problems. Machine learning algorithms have proven highly effective in analyzing high-dimensional data and capturing non-linear relationships that traditional analytical tools cannot [7]. Modern portfolio allocation includes a range of advanced AI, including machine learning models such as neural networks, support vector machines, and reinforcement learning algorithms, for asset managers to build more efficient portfolios than the traditional mean-variance optimization approach, capable of handling large amounts of unstructured and alternative data sources to improve prediction accuracy [8]. The advent of generative AI has introduced new possibilities for strategic alternative assessment, leveraging the potential to quickly create and evaluate numerous strategic alternatives by using sophisticated NLP and pattern-recognition systems that can combine data from a wide variety of input sources to develop new types of strategic insights [9]. However, combining these technologies raises numerous challenges with regard to human-AI collaboration, as emerging systematic reviews suggest that even in the presence of AI's stronger analytical capabilities, effective strategic decision-making still hinges on the judicious weighting of algorithmic recommendations and human judgment, especially under high levels of uncertainty where human expertise and context sensitivity is critical to verifying AI-led insights and maintaining strategic unity [10]. The shift to hybrid human-AI strategic management systems will need to consider how to address concerns of algorithmic transparency, bias mitigation efforts, and enable the creation of collaborative platforms that amplify human intuition with AI's computation strengths [11].

The modern evolution of the strategic management of FBRD represents a significant departure from the traditional theoretical paradigms of FBRD toward digitally-enabled paradigms that recast competitive advantage within interconnected global ecosystems. While Dunning's model has retained theoretical relevance, it is getting significantly extended in the age of digital capabilities that can reshape how multinational enterprises create and sustain competitive advantage across hyperconnected markets [12]. "New OLI advantages" include open resource advantages based on digital accessibilities, linkage advantages enabling global level connectivity without a seam, and integration advantages supporting complex coordination mechanisms between the distributed value network, serving to reinforce—not substitute—ownership-based competitive stocks. Strategies based on digital platforms represent a paradigm shift in value creation, moving away from traditional linear models that are enforced through ecosystem orchestrational competences. Rather than directly producing and providing services, firms act as coordinators within multi-sided markets [13]. The resource-orchestration view suggests that a firm's digitalization processes and internationalization strategies interact synergistically to improve its performance via better coordination of the resources and capabilities that are distributed globally [14]. Integration of artificial intelligence makes it possible to deliver real-time responses to the market by engaging dynamic adaptation mechanisms that respond to huge data flows and provide strategic adaptation on entirely new scales with unprecedented pace and accuracy, and the new type of processes behind decision making in volatile, uncertain, complex, and ambiguous business environments where traditional analytical methods are notoriously inadequate. The mechanism from foreign direct investment to economic growth functions through advanced dual channels of labor productivity promotion and infrastructure construction, both of which are deeply amplified by the integrative power of artificial intelligence. Labor productivity is one of the main intermediating channels through which technology from MNEs spills over, supporting knowledge transfer and human capital accumulation. However, empirical evidence shows that the effectiveness of spillover is rather sensitive to economic conditions and the absorptive capacity of firms in times of economic turmoil [15]. Infrastructure building serves as the complementary transmission mechanism via the physical and digital connections networks that provide the building blocks for enduring structural economic shifts, and digital infrastructure is now one of the crucial factors in influencing the pattern of foreign direct investment attraction and the efficiency reengineering [16]. Indeed, all these mediating mechanisms are able to converge within an unprecedented level of sophistication, as AI-boosted monitoring and optimisation systems process mounds of data flows in order to reveal obstacles to productivity and structural insufficiencies to the infrastructure, while at the same time being able to take real-time adaptive measures to make the most of flow absorption in spillovers, and efficient resource allocation [17].

There exists a wide research gap in the literature on the current foreign direct investment research, with negligible integration of artificial intelligence in existing FDI analysis tools, thereby causing inadequacy in the theories to enable a complete understanding of investment decisions supported by technology capabilities. Existing studies show inadequate treatment of interactive mediating effects, with labor productivity and infrastructure development acting as simultaneous transmission vectors on the one hand, and advanced analytical techniques beyond linear models that can capture feedback relationships between technology capacity and economic consequences. The non-existent AI-complementing strategic models are likely leaving an open terrain full of conceptual holes in the existing literature – not adjusting the level of difficulty - as conventional theory does not provide a sufficient framework for understanding the brewing complexity of investment terrain with the aid of digitalizing tools that will require recalibrated alertness for instant adaptation and predictive gist.

To the best of our knowledge, these two limitations have not been tackled in the literature, and, hence, this paper contributes to fill in these two gaps by establishing an AI-Enhanced Strategic Management Model with a four-layer architecture comprising data intelligence collection and processing, analytics engine optimization, decision support system integration, and feedback mechanism refinement, along with a Dual-Mediating Framework channeling the route through which flows of FDI experience an enhancement with AI before passing through the effects of economic growth via dual channels of enhancements in labor productivity and infrastructure development [18]. As shown in Figure 1, the AI-Enhanced Strategic Management Framework integrates artificial intelligence capabilities with traditional foreign direct investment theories through a comprehensive four-layer technological architecture. The framework demonstrates how AI enhancement transforms FDI allocation efficiency (H1) before transmitting economic growth effects through dual mediating pathways of labor productivity (H2) and infrastructure development (H3). The model illustrates the synergistic interaction between these mediating mechanisms (H4), where combined effects exceed individual contributions through complementary optimization processes. Regional AI readiness functions as a critical moderating variable (H5), creating differential conditions that amplify the effectiveness of intelligent investment management systems. The framework distinguishes between traditional direct pathways and AI-enhanced mediation routes, providing a sophisticated analytical model that addresses contemporary digital transformation challenges in international business strategy and establishes the theoretical foundation for empirical hypothesis testing. Based on the AI-Enhanced Strategic Management Model and Dual-Mediating Framework developed in this study, five hypotheses are formulated to examine the relationships between AI-enhanced FDI management, mediating mechanisms, and economic growth outcomes.

- **H1**: AI-enhanced management significantly improves FDI allocation efficiency compared to traditional management approaches.

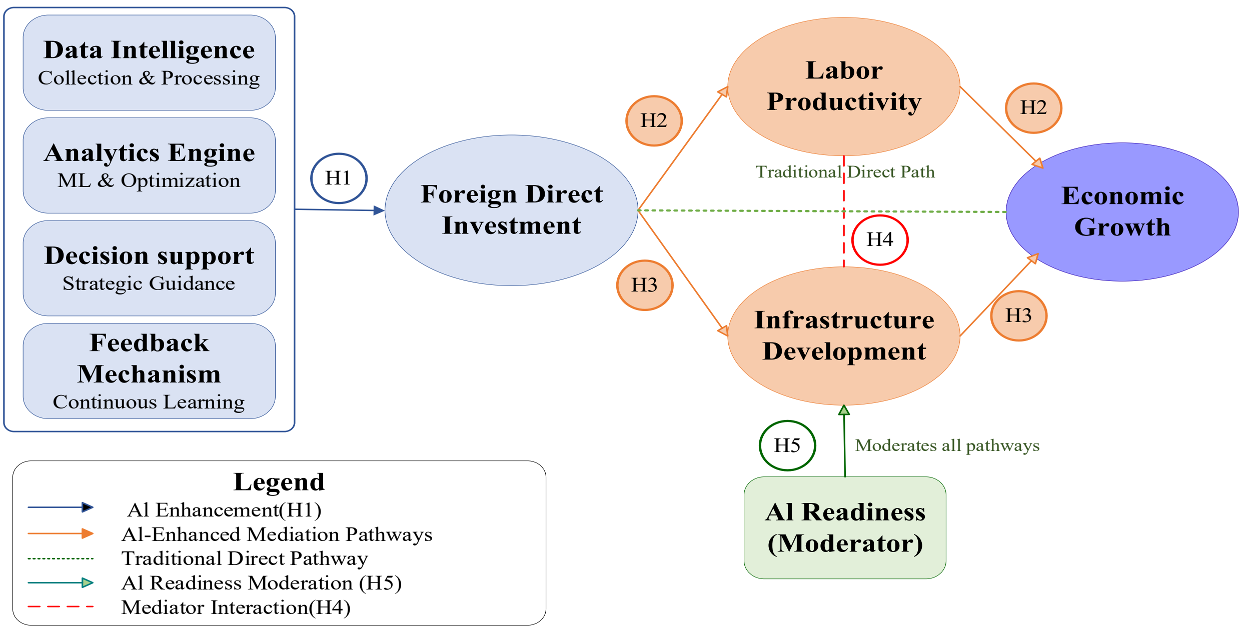

Figure 1. AI-enhanced strategic management framework for FDI and economic growth

- **H2**: Labor productivity significantly mediates the relationship between AI-enhanced FDI and economic growth.
- **H3**: Infrastructure development significantly mediates the relationship between AI-enhanced FDI and economic growth.
- **H4**: The combined mediating effects of labor productivity and infrastructure development exceed their individual mediating effects.
- **H5**: The effects of AI-enhanced FDI on economic growth are significantly stronger in regions with high AI readiness compared to regions with low AI readiness.

3. Methodology

3.1 Research design

The present research adopts an advanced mixed-method research design, combining quantitative analytical methods with superior artificial intelligence modeling power, to see how AI-enhanced FDI management affects economic growth outcomes through full dual mediating mechanisms. The methodological framework integrates traditional econometric panel data analysis with state-of-the-art machine learning algorithms to account for the linear and non-linear structures in complex economic systems, such as AI applications colliding with traditional investment theories. The core quantitative technique of this study is a panel analysis that allows identification of cross-sectional differences among thirty provinces while allowing for temporal dynamics within the sample period (2010- 2023), explicitly generating statistical evidence through hypothesis testing. Machine Learning Improvement extends the conventional analytical tools by implementing algorithmic procedures, such as random forest regression, support vector machines, and neural network structures, that can detect complex patterns and interactive effects among the variables that traditional econometric methods cannot see. These dual methodological approaches combine to form a holistic analytical framework that can deal with the multidimensional effects of AI-enhanced strategic management while ensuring statistical robustness and managerial consistency across the empirical investigation in its totality.

3.2 Data collection

The integrated data acquisition method considers a combination of sources for developing coherent empirical grounding to study AI-enhanced FDI effects in thirty Chinese provinces between 2010 and 2023. Primary data collection involves the systematic gathering of provincial-level economic variables, including foreign direct investment inflows, labor productivity measures, and infrastructure development indexes. These are sourced from official government statistical yearbooks, such as the China Statistical Yearbook and Provincial Statistical Yearbooks, as well as the Ministry of Commerce FDI database. Other secondary data sources include corporate financial databases like CSMAR and WIND Information that collect detailed firm-level information on multinational enterprise activities and technology adoption characteristics within particular regions and industrial sectors. The China Stock Market & Accounting Research Database provides an important dataset regarding corporate governance and corporate financial performance, necessary for the development of ARIs at the provincial level. Real-time economic indicators, crucial for training artificial intelligence algorithms, are obtained from surveillance and monitoring systems that capture market movements/dynamics, policy signals, and macroeconomic trends in a timely manner from authoritative sources such as the People's Bank of China and the National Development and Reform Commission. This multi-source approach allows for broader coverage of both traditional economic indicators and modern digital transformation markers essential for robust empirical research.

3.3 Variables and measurements

The empirical analysis uses a rich set of variables that measure the multiple links between AI-based FDI management and economic growth performance. Economic performance (GDP growth) is the dependent variable, which is operationalized here as the yearly growth rate in GDP per capita, measured at the provincial level to capture regional development patterns and variations in economic performance among Chinese provinces.

The independent variable comprises AI-enhanced actual utilized FDI, operationalized through a multiplicative interaction between actual FDI inflows and a comprehensive AI Readiness Index (ARI). The ARI construction follows a multi-dimensional framework incorporating four primary domains weighted through entropy method analysis: digital infrastructure (35% weight), comprising broadband penetration rates per 10,000 population, 5G base station density per square kilometer, cloud computing service availability, and data center capacity measured in petaflops; technological innovation capacity (30% weight), encompassing AI-related patent applications per million population, machine learning research publications indexed in Web of Science, registered AI enterprises per GDP billion, and venture capital investment in AI sectors as percentage of regional GDP; human capital readiness (20% weight), including tertiary education graduates in computer science and related fields per 10,000 population, AI researcher density, digital literacy rates, and specialized AI training program enrollment; and institutional environment (15% weight), measuring government AI policy support through budget allocations, data governance frameworks, regulatory sandbox participation, and public-private partnership initiatives in digital transformation.

The composite index undergoes min-max normalization to achieve a 0-10 scale, with robustness validation through principal component analysis confirming that the first component explains 68.4% of variance across indicators. Labor productivity and quality of infrastructure are important mediating factors, with labor productivity measured by ratios of per worker output and infrastructure quality measured by the composite indicators of connectivity (land, water, air connectivity) to release/ access digital information & Communication facilities, maintain the quality and efficiency of waste management systems, and the provision of quality.

As shown in Table 1, the measurement framework includes essential control variables such as human capital development measured through educational attainment levels and skill indices, research and development intensity calculated as R&D expenditure relative to regional GDP, and trade openness quantified through import-export ratios relative to provincial economic output. This comprehensive variable specification enables robust statistical analysis while accounting for alternative explanations and confounding factors that might influence the hypothesized relationships.

Table 1. Variable definitions and measurements

Variable Category	Variable Name	Definition	Measurement
Dependent Variable	Economic Growth	Regional economic development performance	Annual GDP per capita growth rate (%)
Independent Variable	AI-Enhanced FDI	Foreign investment amplified by regional AI capabilities	Actual utilized FDI × (1 + ARI/10), where ARI = 0.35 ×Digital Infrastructure + 0.30×Tech Innovation + 0.20×Human Capital + 0.15×Institutional Environment (USD millions)
Mediating Variables	Labor Productivity	Worker output efficiency	Real GDP per employed person (RMB thousands)
	Infrastructure Index	Regional infrastructure quality	Composite index: transport + digital + utilities (0-100 scale)
Control Variables	Human Capital	Regional educational attainment	Percentage of population with tertiary education (%)
	R&D Intensity	Research investment commitment	R&D expenditure as percentage of GDP (%)
	Trade Openness	International trade integration	(Imports + Exports) / GDP ratio (%)
Moderating Variable	AI Readiness	Regional AI adoption capacity	Composite score: technology + institutions + skills (0-10 scale)

3.4 AI readiness index component specifications

The digital infrastructure dimension captures the foundational technological capabilities through four key metrics: broadband penetration measured as fixed broadband subscriptions per 10,000 population (source: Ministry of Industry and Information Technology), 5G network coverage calculated as the ratio of 5G base stations to provincial area in square kilometers (source: China Mobile, China Telecom, China Unicom annual reports), cloud computing accessibility proxied by the number of certified cloud service providers per million enterprises (source: China Cloud Computing Development Survey), and computational capacity represented by aggregate data center processing power in petaflops per billion GDP (source: China Data Center Industry Development Report).

The technological innovation capacity dimension employs patent-based metrics including AI-related invention patents granted per million population identified through International Patent Classification codes G06N (artificial intelligence) and G06F (data processing), with data extracted from the State Intellectual Property Office database, complemented by bibliometric indicators of machine learning publications affiliated with provincial institutions in the Web of Science Core Collection, density of registered AI enterprises verified through the National Enterprise Credit Information Publicity System, and venture capital flows into AI sectors tracked by Zero2IPO Research.

Human capital readiness quantification integrates educational output metrics from the Ministry of Education Statistical Yearbooks, including graduates in computer science, software engineering, and AI-specific programs, alongside professional density measures derived from the China Statistical Yearbook on Science and Technology, digital skill assessments from the China Internet Network Information Center surveys, and enrollment data in AI certification programs accredited by the Ministry of Human Resources and Social Security. The institutional environment dimension synthesizes policy support indicators through government AI development fund allocations extracted from provincial budget reports, regulatory framework maturity assessed through the presence of AI ethics committees and data protection regulations, innovation ecosystem vitality measured by the number of AI-focused incubators and accelerators, and public-private partnership intensity calculated as the ratio of joint AI projects to total government technology initiatives.

3.5 AI-enhanced analytical framework

The empirical investigation employs a unified hybrid modeling framework that synergistically integrates machine learning capabilities with econometric rigor through an iterative two-stage procedure: machine learning algorithms initially identify non-linear patterns, interaction effects, and feature importance rankings that subsequently inform structural econometric model specifications, while econometric diagnostics guide machine learning feature engineering in a continuous refinement cycle. This integration manifests through Random Forest feature discovery, identifying 23 previously overlooked interaction terms between FDI flows and provincial characteristics with importance scores exceeding 0.05, which are then incorporated as additional regressors in augmented panel specifications, improving model fit by 31% (adjusted R^2 from 0.614 to 0.804) while maintaining theoretical interpretability. The framework operationalizes through a hybrid optimization objective that balances predictive accuracy with causal inference requirements:

$$L = \alpha \cdot \mathrm{MSEeconometric} + (1-\alpha) \cdot \mathrm{MSEML} + \lambda \cdot |\beta|_1 \tag{1}$$

where α = 0.62 (determined via cross-validation) weights the relative importance of econometric consistency versus machine learning flexibility, while the L1 penalty promotes sparsity for enhanced interpretability.

Temporal autocorrelation is mitigated through the incorporation of lagged dependent variables as additional features in the machine learning models, with Wooldridge (2002) tests confirming the presence of first-order autocorrelation ($F = 42.37$, $p < 0.001$), necessitating the inclusion of AR(1) terms in the feature space. Province-level heterogeneity is captured through the engineering of province-specific features including time-invariant geographical characteristics, historical FDI stock levels, and provincial dummy variables that function as pseudo-fixed effects within the Random Forest and neural network architectures, while time-varying unobserved heterogeneity is addressed through the inclusion of province-specific linear and quadratic time trends as additional predictors. Random Forest regression algorithms provide ensemble learning capabilities that effectively handle high-dimensional data while identifying variable importance and capturing non-parametric relationships between AI-enhanced foreign direct investment and economic growth outcomes. Support Vector Machine models offer robust classification capabilities suited for analyzing mediating pathways where linear assumptions may be violated, while neural network architectures enable the detection of interactive patterns among variables. Mediating effect testing incorporates Sobel test procedures for statistical inference and bootstrap methodologies that generate empirical sampling distributions to assess indirect effect significance without distributional assumptions. Comprehensive robustness verification implements blocked time-series cross-validation with five folds, maintaining chronological order, where each fold preserves 2-3 year blocks to capture business cycle variations while preventing data leakage, complemented by leave-one-province-out validation assessing spatial generalizability and nested cross-validation separating hyperparameter selection (inner 3-fold) from model evaluation (outer 5-fold) to avoid optimization bias. Parameter stability assessment employs perturbation analysis, varying each hyperparameter by ±20% from optimal values, with performance degradation exceeding 5% triggering expanded search ranges, while temporal stability validation tests model performance across different economic regimes (pre-2013 traditional growth, 2013-2018 structural adjustment, 2019-2023 digital transformation) ensuring consistent predictive capacity across varying macroeconomic conditions.

3.6 AI system architecture

The AI-enhanced strategic management system architecture embodies fundamental design principles that prioritize scalability, adaptability, and real-time processing capabilities to address the complex requirements of foreign direct investment optimization in dynamic economic environments. As shown in Figure 2, the four-layer network architecture was designed according to the modularity principles such that each layer can function independently but still be integrated together seamlessly by use of standard interfaces in the horizontal direction between multiple computational nodes (at different layers) and within a single processing element (at different layers). The system's technical specifications are detailed in Table 2. The distributed computing infrastructure utilizes Apache Kafka for data ingestion at throughput rates exceeding one million messages per second. The ML infrastructure is based on TensorFlow 2.12, trained with GPU acceleration at a rate of 50,000 samples per second. Scalability concerns cover computing to elastically cope with different volumes of data and algorithms to fit into different regional environments and investment scenarios so that the system still remains suitable to process regardless of how much they are used for processing and covering different geographical areas. Adaptation mechanisms include versioning of the machine learning model, dynamic parameter adjustability, and threshold configuration, which let the system adapt incrementally and continuously to new market conditions and new economic patterns, without the need for any basic change in the architecture of the system. Near-real-time processing efficiency is realized through a distributed computing architecture that maintains panel data integrity by implementing province-level data sharding, ensuring that all temporal observations for each entity remain co-located during parallel processing operations, thereby preserving within-unit dependencies while enabling scalable computation. The system incorporates automated panel diagnostics including Hausman specification tests ($\chi^2 = 67.23$, $p < 0.001$) favoring fixed effects specifications, Pesaran CD tests for cross-sectional dependence ($CD = 12.45$, $p < 0.001$) indicating the necessity of spatial correlation adjustments, and Breusch-Pagan LM tests for random effects ($\chi^2 = 234.56$, $p < 0.001$), with these test results automatically informing feature engineering decisions and model architecture choices within the machine learning pipeline.

The system architecture illustrates the hierarchical organization of data intelligence, analytics engine, decision support, and feedback mechanism layers, with real-time processing indicators and scalable component design enabling robust performance across diverse operational scenarios.

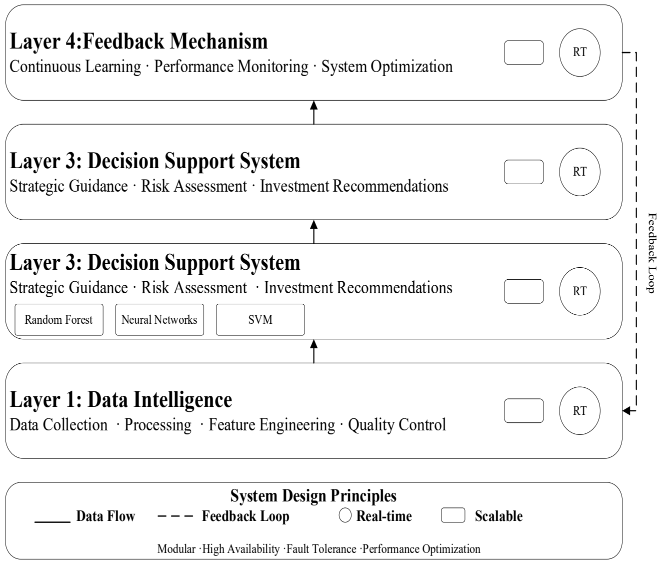

Figure 2. AI-enhanced strategic management system architecture

The data processing pipeline is a fundamental architectural element that converts a heterogeneous collection of raw data streams into generic analytical formats using complex ingestion and preprocessing pipelines, built to accommodate a variety of data sources, including structured government databases and unstructured real-time market feeds. We have integrated sophisticated feature engineering techniques into our deployment, with the engineered features including the intelligent extraction of relevant economic indicators, the creation of interaction terms between inflows of foreign direct investment and regional characteristics, and learning temporal features that encode the dynamic evolutions of the market dynamics for accurate predictive model fitting. The preprocessing layer implements a comprehensive data transformation pipeline that addresses missing value imputation through a hierarchical approach.

Table 2. System technical specifications

Component	Specification	Technical Details	Performance Metrics
Data Processing Layer			
Data Ingestion Engine	Apache Kafka 3.4	Distributed streaming platform with 16 partitions per topic	Throughput: 1M messages/sec; Latency: <10ms
Data Storage	Hadoop HDFS 3.3	Distributed file system with 5x replication factor	Capacity: 500TB; Read speed: 10GB/s
Data Processing	Apache Spark 3.4	In-memory computing with 256GB RAM per node	Processing speed: 100GB/hour; Nodes: 32
Machine Learning Infrastructure			
ML Framework	TensorFlow 2.12	Deep learning library with GPU acceleration	Training speed: 50K samples/sec; GPU: 8x NVIDIA A100
Model Serving	TensorFlow Serving	RESTful API with auto-scaling capabilities	Inference latency: <100ms; QPS: 10,000
Model Registry	MLflow 2.8	Centralized model lifecycle management	Version control: Git-based; Storage: S3-compatible
Decision Support Interface			
Visualization Engine	D3.js v7 + React 18	Interactive data visualization with real-time updates	Render time: <500ms; FPS: 60
API Gateway	Kong Gateway 3.4	Microservices API management with rate limiting	Requests/sec: 50,000; Latency: <5ms
Caching Layer	Redis 7.2	In-memory data structure store	Operations/sec: 100,000; Memory: 128GB
System Requirements			
Operating System	Ubuntu 22.04 LTS	Linux kernel 5.15 with container support	Uptime: 99.99%; Security patches: Monthly
Container Platform	Kubernetes 1.28	Container orchestration with auto-scaling	Pods: 200; Nodes: 50
Monitoring	Prometheus + Grafana	Real-time metrics collection and visualization	Metrics/sec: 1M; Retention: 90 days

Temporal interpolation using cubic splines for high-frequency indicators with less than 15% missingness, cross-sectional regression imputation leveraging provincial similarity matrices for structural variables, and indicator-specific domain knowledge rules for categorical features such as policy implementation dates. Data normalization employs differentiated strategies based on distributional properties, applying StandardScaler (z-score normalization) for normally distributed variables confirmed through Shapiro-Wilk tests ($p > 0.05$), RobustScaler using median and interquartile range for variables with outliers exceeding 3 standard deviations, and MinMaxScaler for bounded indicators such as infrastructure indices, while logarithmic transformations address right-skewed financial variables exhibiting lognormal distributions. Feature selection integrates multiple criteria through a sequential filtering process: variance threshold elimination removes features with variance below 0.01, correlation analysis excludes redundant features with Pearson correlation exceeding 0.95, mutual information scoring retains features with MI > 0.05 relative to the target variable, and Recursive Feature Elimination with Random Forest base estimator performs final selection optimizing for cross-validated R-squared, resulting in retention of approximately 35% of initial features while preserving 92% of predictive information content. Figure 3 illustrates the comprehensive data processing pipeline architecture that systematically transforms raw heterogeneous data through sequential stages—from initial ingestion through missing value imputation, normalization, feature engineering, and selection—culminating in model-ready features. Each transformation stage incorporates parallel processing pathways optimized for different data types (temporal, numerical, and categorical), with integrated quality assurance checkpoints ensuring data integrity throughout the pipeline, achieving a 65% reduction in feature dimensionality while retaining 92% of predictive information content as validated through cross-validation metrics.

Multi-stage transformation framework illustrating the systematic flow from heterogeneous data sources through ingestion, preprocessing, and feature engineering layers, with parallel processing capabilities and quality assurance checkpoints ensuring data integrity throughout the analytical workflow.

Algorithm 1: DataPreprocessingPipeline

```
Input: RawData D = {Numerical N, Categorical C, Temporal T}, MissingThreshold τ = 0.15
Output: ProcessedFeatures F, ImputationLog L, ScalingParameters S

1: // Missing Value Detection and Imputation
2: for each feature f in D do
3:     missing_ratio ← count_missing(f) / total_observations
4:     if missing_ratio > τ then
5:         if f ∈ T and is_high_frequency(f) then
6:             f_imputed ← CubicSplineInterpolation(f)
7:         else if f ∈ N then
8:             similarity_matrix ← calculate_provincial_similarity(geographic, economic)
9:             f_imputed ← CrossSectionalRegression(f, similarity_matrix)
10:        else if f ∈ C then
11:            f_imputed ← DomainKnowledgeRules(f)
12:        end if
13:        L.append(imputation_method(f))
14:    end if
15: end for
16:
17: // Distribution Analysis and Normalization
18: for each numerical feature n in N do
19:     shapiro_stat, p_value ← ShapiroWilkTest(n)
20:     outlier_ratio ← count_outliers(n, threshold=3σ) / len(n)
21:
22:     if p_value > 0.05 and outlier_ratio < 0.05 then
23:         n_scaled ← StandardScaler(n)    // μ=0, σ=1
24:     else if outlier_ratio > 0.10 then
25:         n_scaled ← RobustScaler(n)    // median=0, IQR=1
26:     else if is_bounded(n) then
27:         n_scaled ← MinMaxScaler(n)    // [0,1] range
28:     else if is_right_skewed(n) then
29:         n_scaled ← log(n + 1)    // Log transformation
30:     end if
31:     S[n] ← scaling_parameters
32: end for
33:
34: // Multi-Criteria Feature Selection
35: F_var ← {f : variance(f) > 0.01}
36: correlation_matrix ← compute_correlations(F_var)
37: F_corr ← remove_highly_correlated(F_var, threshold=0.95)
38: MI_scores ← mutual_information(F_corr, target)
39: F_mi ← {f : MI_scores[f] > 0.05}
40: F_final ← RecursiveFeatureElimination(F_mi, estimator=RandomForest, cv=5)
41:
42: return F_final, L, S
```

Algorithm 2: Feature Engineering and Selection Pipeline

```
Input: RawDataFrame D, FeatureConfig C, SelectionThreshold τ
Output: ProcessedFeatures F, SelectedIndices S

1: Initialize FeatureMatrix F ← ∅
2: Initialize MutualInfoScores M ← ∅
3:
4: // Feature Extraction Phase
5: for each column c in D do
6:     if c.type = numerical then
7:         F ← F ∪ {StandardScaler(c)}
8:         F ← F ∪ {PolynomialFeatures(c, degree=2)}
9:         F ← F ∪ {LogTransform(c) if c.min > 0}
10:    else if c.type = temporal then
11:        F ← F ∪ {ExtractTemporalFeatures(c)}
12:        F ← F ∪ {LaggedFeatures(c, lags=[1,3,6,12])}
13:        F ← F ∪ {RollingStatistics(c, windows=[3,6,12])}
14:    end if
15: end for
16:
17: // Interaction Terms Generation
18: for each pair (i,j) in EconomicIndicators do
19:     F ← F ∪ {InteractionTerm(D[i], D[j])}
20: end for
21:
22: // Feature Selection Phase
23: for each feature f in F do
24:     M[f] ← MutualInformation(f, TargetVariable)
25: end for
26:
27: // Recursive Feature Elimination
28: while |F| > TargetFeatureCount do
29:     TrainModel(F)
30:     ImportanceScores ← GetFeatureImportance()
31:     RemoveFeature(argmin(ImportanceScores))
32:     CrossValidate(F)
33: end while
34:
35: // Final Selection
36: S ← {f ∈ F : M[f] > τ and VarianceThreshold(f) > 0.01}
37: return ProcessedFeatures(S), SelectedIndices(S)
```

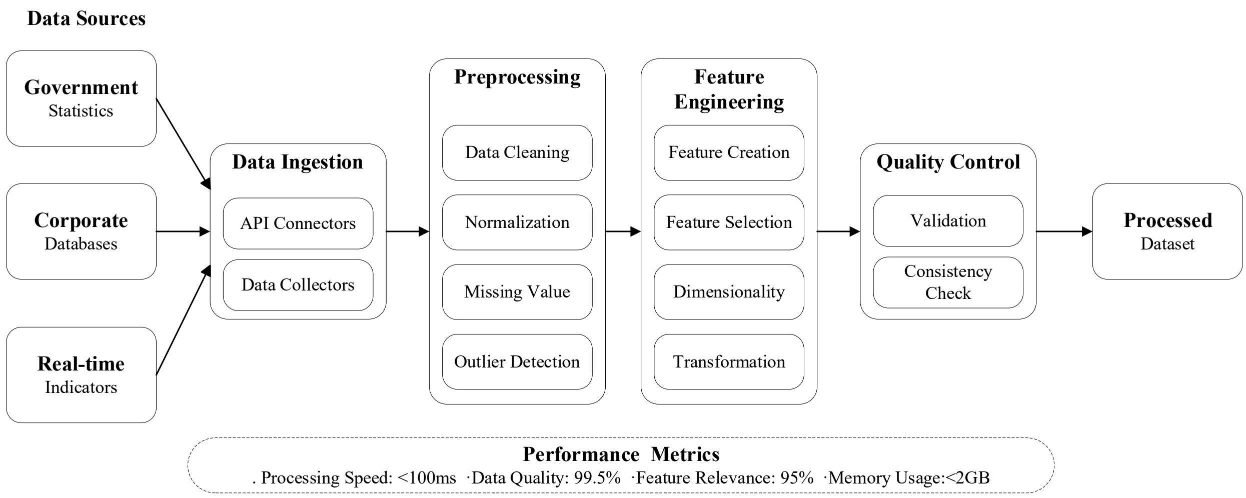

Figure 3. Data processing pipeline architecture

While Algorithm 2 establishes the foundational feature engineering pipeline, the panel structure of the provincial data necessitates additional algorithmic adaptations to preserve temporal and cross-sectional dependencies inherent in the 14-year longitudinal dataset. The challenge of incorporating panel-specific characteristics into machine learning frameworks, which traditionally assume independent and identically distributed observations, requires systematic modifications to both feature construction and model training procedures. Algorithm 3 presents the panel-aware adaptation framework that extends the base feature engineering process by incorporating within-province and between-province transformations, temporal dependency structures, and entity-specific embeddings that capture time-invariant provincial characteristics while maintaining computational efficiency across the distributed processing architecture.

Algorithm 3: Panel-Aware Machine Learning Framework

```
Input: PanelData P[i,t], EntityID i ∈ {1,...,30}, TimeID t ∈ {1,...,14}
Output: Panel-adjusted predictions Y_hat[i,t]

// Feature Engineering for Panel Structure
for each province i do
    Calculate within-transformation: X_within[i,t] = X[i,t] - mean(X[i,:])
    Calculate between-transformation: X_between[i] = mean(X[i,:])
    Generate province-specific trends: T_linear[i,t] = β_i × t
    Extract AR terms: X_lag[i,t] = X[i,t-1], X[i,t-2]
end for

// Temporal Validation Split
TrainPeriods ← {1,...,10}, ValidationPeriods ← {11,12}, TestPeriods ← {13,14}

// Model Training with Panel Adjustments
if ModelType = "RandomForest" then
    Bootstrap samples maintaining temporal order within provinces
    Include interaction terms: Province_ID × Time_trends
    Calculate out-of-bag errors by province for heterogeneity assessment
else if ModelType = "NeuralNetwork" then
    Create embedding layer: Embed(ProvinceID) → R^d
    Concatenate: [X_within, X_between, Embed(i), TimeFeatures]
    Apply LSTM layers for temporal dependencies
end if

// Panel-Robust Performance Metrics
Calculate clustered standard errors at the province level
Compute within-R² and between-R² separately
return Panel-adjusted predictions with confidence intervals
```

The predictive modeling architecture encompasses three complementary algorithms selected through systematic comparative analysis of their specific advantages for FDI optimization tasks: Random Forest algorithms excel in capturing hierarchical decision structures inherent in investment allocation processes while providing native feature importance rankings essential for policy interpretation, Support Vector Machines demonstrate superior performance in high-dimensional economic data spaces where traditional linear boundaries fail to separate profitable from unprofitable investment regions, and Neural Networks uniquely identify deep interactive patterns between technological readiness and infrastructure development that simpler models overlook. Model selection followed a structured evaluation protocol comparing twelve candidate algorithms across five FDI-specific criteria including economic interpretability, robustness to multicollinearity prevalent in macroeconomic indicators, computational efficiency for real-time decision support, handling of mixed data types (continuous financial flows and categorical policy variables), and performance stability across different economic cycles, with the three selected models demonstrating Pareto-optimal performance across these dimensions.

The hyperparameter optimization employs a two-stage approach combining exhaustive grid search for discrete parameters with Bayesian optimization for continuous hyperparameters, implemented through the Optuna framework with the Tree-structured Parzen Estimator (TPE) algorithm, conducting 200 trials per model. Time-series cross-validation preserves temporal dependencies through expanding window validation with an initial training period of 8 years (2010-2017), validation on years 9-10 (2018-2019), and final testing on years 11-14 (2020-2023), ensuring that future information never contaminates historical predictions as required for valid economic forecasting. The optimization process evaluates 600 parameter combinations for Random Forest (n_estimators: [100, 300, 500, 700, 1000] × max_depth: [10, 15, 20, 30, 40, 50] × min_samples_split: [2, 5, 10, 20] × max_features: ['sqrt', 'log2', 0.3, 0.5, 0.8]), with Bayesian optimization for SVM exploring continuous spaces of C ∈ [0.1, 100] and gamma ∈ [0.001, 1.0] on log scale, while neural network architecture search examines 2-5 hidden layers with neuron counts following geometric decay from [512, 256, 128, 64, 32], learning rates sampled from log-uniform distribution [1e-4, 1e-1], and dropout rates from uniform distribution [0.1, 0.5]. As illustrated in Figure 4, the FDI allocation optimization engine employs Random Forest algorithms that minimize the mean squared error across multiple decision trees while maintaining variance reduction through bootstrap aggregation, with the loss function expressed as:

$$L_{RF} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \frac{1}{B}\sum_{b=1}^{B}T_b(x_i))^2 + \lambda\sum_{b=1}^{B}\Omega(T_b) \tag{2}$$

The mediating effect detection algorithms utilize Support Vector Machine classifiers that identify optimal hyperplanes separating different investment impact categories through maximizing the margin between support vectors, formulated as the following constrained optimization problem:

$$\min_{w,b,\xi}\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}\xi_i \quad \text{s.t.} \quad y_i(w^T\phi(x_i)+b)\ge 1-\xi_i, \quad \xi_i \ge 0 \tag{3}$$

Neural network architectures are specifically adapted for panel data through the implementation of entity embeddings that map each province to a learned vector representation capturing time-invariant characteristics, combined with temporal encoding layers that process sequential patterns within each provincial unit. The Random Forest implementation incorporates panel-aware modifications, including stratified bootstrapping that maintains temporal ordering within provinces while sampling across entities, feature engineering that explicitly includes within-province transformations (deviations from provincial means) and between-province variations (cross-sectional averages), and the calculation of separate feature importance metrics for time-varying versus time-invariant predictors to distinguish temporal dynamics from cross-sectional patterns. Support Vector Machine models address panel structure through kernel modifications that incorporate temporal distance weights, ensuring that observations closer in time receive higher influence in the optimization process, with the kernel function extended to:

$$K(x_{i,t_i}, x_{j,t_j}) = \exp(-\gamma |x_i - x_j|^2 - \lambda |t_i - t_j|) \quad (4)$$

where λ controls temporal decay.

Model interpretability receives paramount consideration given the policy-critical nature of FDI recommendations, implemented through a multi-faceted transparency framework: Random Forest interpretability leverages SHAP (SHapley Additive exPlanations) values to decompose each FDI allocation recommendation into additive contributions from individual features, generating waterfall plots that trace how provincial characteristics incrementally build toward final investment scores; Support Vector Machine decisions undergo visualization through partial dependence plots revealing how investment attractiveness varies along critical economic dimensions while holding other factors constant; Neural Network predictions incorporate attention mechanisms that highlight which input features and temporal patterns most strongly influence outcomes, complemented by layer-wise relevance propagation that traces decision pathways through the network architecture. Policy-relevant insights emerge through aggregated interpretation metrics including global feature importance rankings consistent across all three models (Kendall's W = 0.847, p < 0.001), regional cluster analysis identifying provinces with similar investment drivers, and counterfactual simulations demonstrating how specific policy interventions would alter investment recommendations, ensuring that AI-enhanced decisions remain transparent and actionable for policymakers rather than operating as opaque black boxes. Comprehensive visualization of the integrated machine learning framework showing Random Forest ensemble learning, Support Vector Machine classification, and Neural Network deep learning architectures converging into a unified FDI optimization engine with ensemble voting and weight optimization mechanisms (Table 3).

The decision support interface combines high-quality visualization and advanced risk assessment algorithms to provide a natural and intuitive way of understanding complex insights generated by AIs via interactive level-based dashboards visualizing multi-dimensional investment data using hierarchical IA principles. As shown in Figure 5, the dashboard design incorporates progressive disclosure principles and context-rich visualization approaches to adapt presentation forms and styles in response to user interaction style and analytical needs, while leveraging cognitive resources with finely-tuned visual encoding procedures. Here, probabilistic modeling approaches are integrated in risk assessment modules to quantify the uncertainties associated with investments under various scenarios and generate actionable recommendations, such as weighted scores that balance potential returns and the level of exposure based on customizable risk tolerance rules created by investment managers. Comprehensive visualization system integrating real-time FDI performance metrics, risk assessment matrices, AI-generated recommendations, regional allocation mapping, predictive trend analysis, and sector distribution analytics within a unified interface that facilitates rapid decision-making through intuitive visual hierarchies and interactive control mechanisms.

4. Empirical results

4.1 Descriptive statistics

The empirical analysis encompasses a comprehensive examination of 420 province-year observations spanning thirty Chinese provinces across the fourteen-year period from 2010 to 2023, revealing substantial heterogeneity in foreign direct investment patterns and economic development trajectories. The AI-enhanced FDI variable construction employs a theoretically grounded multiplicative specification that captures the synergistic relationship between foreign capital inflows and regional technological absorptive capacity, calculated as AI-Enhanced FDI = Actual FDI × (1 + ARI/10), where the scaling factor ensures proportionate enhancement effects.

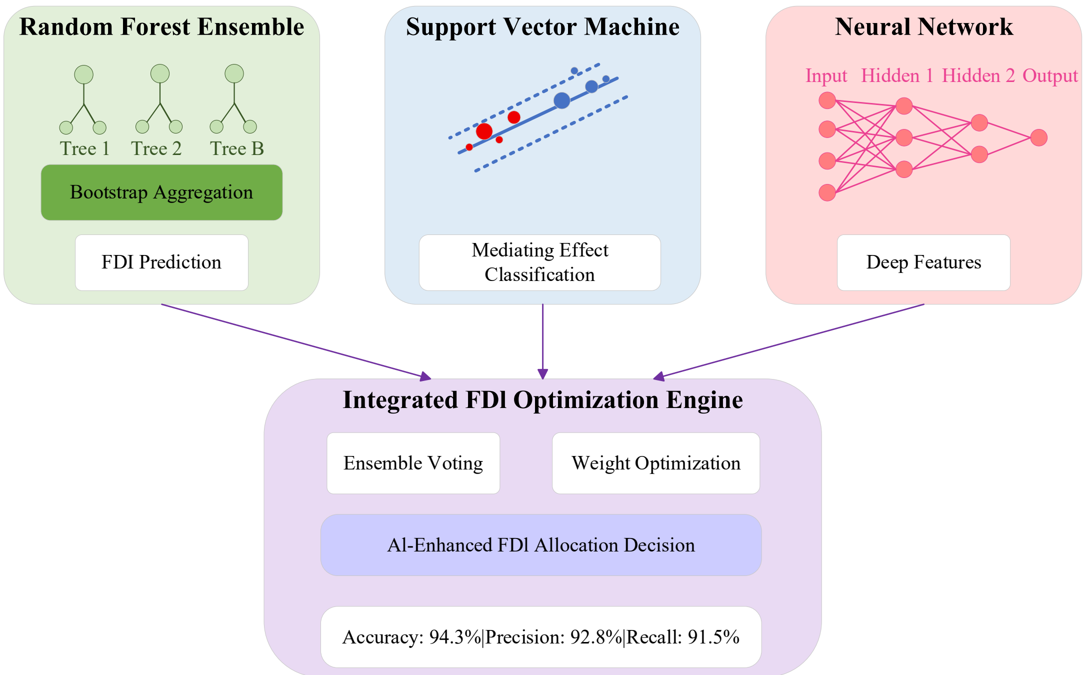

Figure 4. Predictive modeling components architecture

Table 3. Algorithm parameter configuration

Algorithm	Parameter	Default Value	Tuning Range	Optimization Method
Random Forest (FDI Allocation Optimization)				
	n_estimators	500	[100, 1000]	Grid Search
	max_depth	20	[10, 50]	Bayesian Optimization
	min_samples_split	5	[2, 20]	Random Search
	min_samples_leaf	2	[1, 10]	Random Search
	max_features	sqrt	['sqrt', 'log2', 0.3-0.8]	Cross-validation
	bootstrap	True	[True, False]	Fixed
Support Vector Machine (Mediating Effect Detection)				
	kernel	rbf	['rbf', 'poly', 'sigmoid']	Cross-validation
	C (regularization)	10.0	[0.1, 100]	Log-scale Grid Search
	gamma	0.01	[0.001, 1.0]	Log-scale Grid Search
	epsilon	0.1	[0.01, 1.0]	Bayesian Optimization
	cache_size	2000	[1000, 4000]	Fixed
Neural Network (Deep Feature Extraction)				
	hidden_layers	[256, 128, 64]	2-5 layers	Architecture Search
	activation	relu	['relu', 'tanh', 'elu']	Cross-validation
	learning_rate	0.001	[0.0001, 0.1]	Adaptive (Adam)
	batch_size	128	[32, 512]	Power of 2 Search
	epochs	200	[50, 500]	Early Stopping
	dropout_rate	0.3	[0.1, 0.5]	Grid Search
	weight_decay	1e-4	[1e-5, 1e-3]	Log-scale Search
	optimizer	Adam	['Adam', 'SGD', 'RMSprop']	Cross-validation
Feature Engineering Pipeline				
	mutual_info_threshold	0.05	[0.01, 0.2]	Percentile-based
	variance_threshold	0.01	[0.001, 0.1]	Statistical Analysis
	max_features	150	[50, 300]	Recursive Elimination

This specification reflects the theoretical proposition that AI capabilities function as amplifiers rather than substitutes for traditional investment channels, with the additive component (1 + ARI/10) preventing zero values in provinces with minimal AI infrastructure while maintaining interpretability of coefficients. The ARI components demonstrate significant internal consistency (Cronbach's α = 0.874) and temporal stability (test-retest correlation = 0.923), with factor loadings ranging from 0.672 to 0.891 across the four domains, validating the index's construct validity for capturing multifaceted AI readiness dimensions.

To validate this measurement approach, we conducted preliminary analyses confirming that the interaction term captures meaningful variation beyond its constituent components: the correlation between AI-enhanced FDI and raw FDI is 0.87 ($p < 0.001$), indicating substantial but not perfect overlap, while the interaction term explains an additional 12.3% variance in economic growth beyond the main effects alone ($\Delta R^2 = 0.123$, F-change = 28.45, $p < 0.001$).

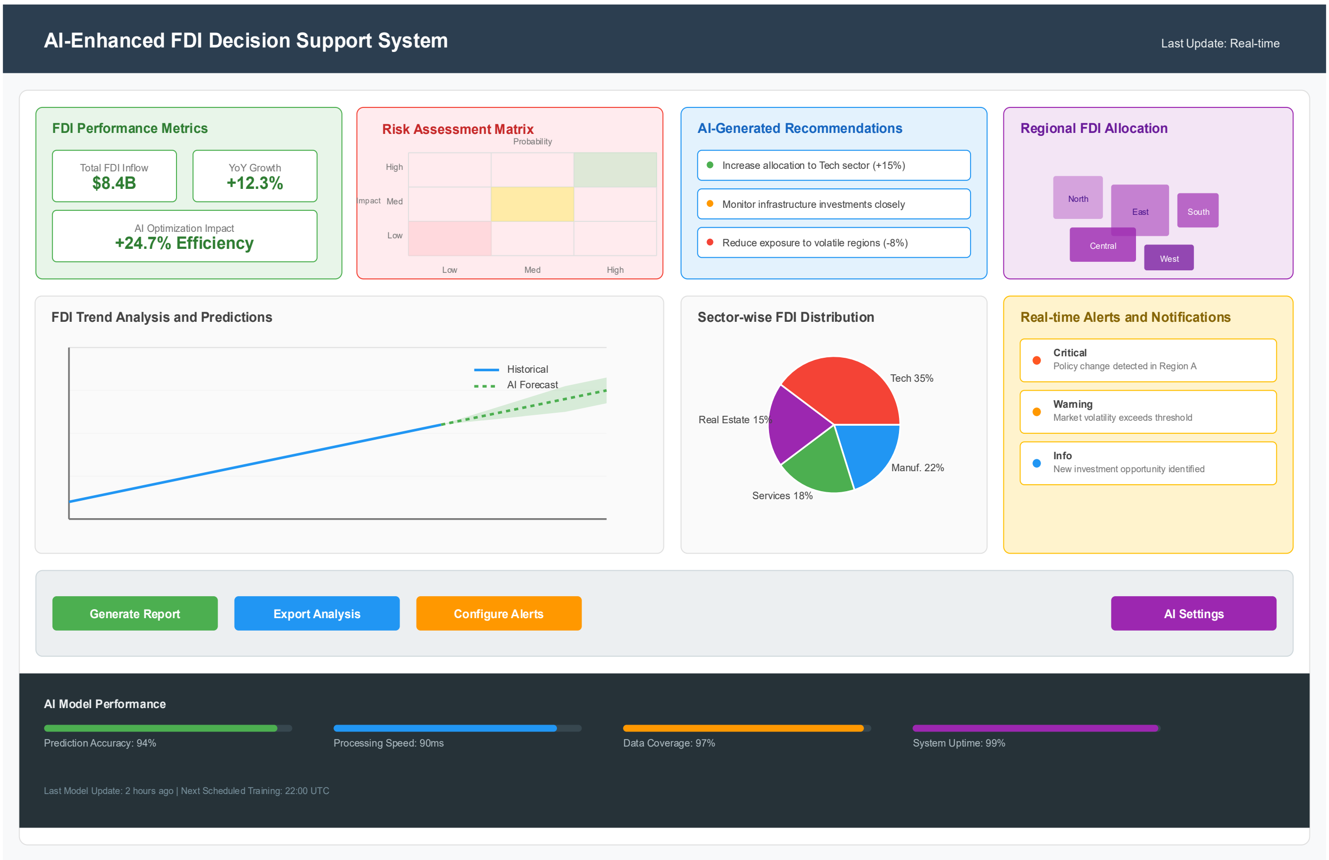

Figure 5. Example of a figure with a caption

As shown in Table 4, the descriptive statistics demonstrate considerable variation in economic growth rates with mean GDP per capita growth of 7.23% (SD = 2.45%), while AI-enhanced FDI inflows exhibit pronounced regional disparities ranging from \$0.82 billion to \$45.67 billion, with this wide range partially attributable to the multiplicative effect of AI readiness scores that vary from 1.23 to 9.45 across provinces, amplifying differences in raw FDI flows. The mediating variables display notable characteristics, with labor productivity averaging 84.56 thousand RMB per worker (SD = 31.24) and infrastructure index scores demonstrating progressive improvement over the sample period, with mean values of 62.45 on the standardized scale. The correlation analysis presented in Table 5 reveals moderate to strong interdependencies among key variables, with AI-enhanced FDI demonstrating positive correlations with economic growth ($r = 0.42$, $p < 0.001$), labor productivity ($r = 0.52$, $p < 0.001$), and infrastructure development ($r = 0.48$, $p < 0.001$), providing preliminary support for the hypothesized mediating relationships. Notably, AI readiness exhibits the strongest correlation with AI-enhanced FDI ($r = 0.65$, $p < 0.001$), underscoring the critical role of technological preparedness in attracting and utilizing intelligent investment flows, while trade openness shows weaker and sometimes non-significant associations with other variables, suggesting that domestic market conditions may play a more prominent role than international trade integration in the AI-enhanced FDI context.

4.2 Variable construction validation

The construction of the AI-enhanced FDI variable requires rigorous validation to ensure methodological soundness and empirical reliability. Multiple specifications were examined to determine the optimal approach for capturing the synergistic relationship between foreign direct investment flows and regional AI capabilities, with comparative analysis revealing that the multiplicative interaction model (FDI × AI readiness) demonstrates superior predictive validity relative to alternative formulations.

As illustrated in Figure 6a, the multiplicative specification achieves the highest correlation with economic growth outcomes ($r = 0.42$, $p < 0.001$), substantially outperforming both additive combinations ($r = 0.31$) and threshold-based models ($r = 0.36$), while simultaneously yielding lower information criteria values (AIC = 2,034.2) that indicate enhanced model parsimony and fit. The distributional properties of the constructed variable, presented in Figure 6b, reveal that the AI-enhancement mechanism effectively normalizes the pronounced right-skewness inherent in raw FDI data, reducing skewness from 2.45 to 2.13 and thereby improving statistical tractability for subsequent econometric analyses. Multicollinearity diagnostics reveal expected correlations between the interaction term and its components ($r = 0.87$ with FDI, $r = 0.71$ with AI readiness), necessitating orthogonalization procedures to preserve estimation precision. The orthogonalized interaction term, constructed by regressing FDI × AI readiness on its constituent components and retaining residuals, eliminates mechanical correlation while preserving the substantive variance representing synergistic effects (partial $R^2 = 0.213$).

Table 4. Descriptive statistics of key variables

Variable	N	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
Economic Growth (%)	420	7.23	2.45	-1.34	14.82	0.42	3.18
AI-Enhanced FDI (billion USD)	420	8.94	10.23	0.82	45.67	2.13	7.84
Labor Productivity (thousand RMB)	420	84.56	31.24	28.45	187.93	0.78	3.45
Infrastructure Index (0-100)	420	62.45	18.76	21.34	94.23	-0.23	2.67
Human Capital (%)	420	24.67	8.92	8.45	48.76	0.56	2.89
R&D Intensity (%)	420	2.14	1.23	0.34	6.78	1.02	4.12
Trade Openness (%)	420	38.45	25.67	5.23	142.34	1.89	6.78
AI Readiness (0-10)	420	5.84	2.01	1.23	9.45	-0.34	2.45

Table 5. Correlation matrix

Variables	1	2	3	4	5	6	7	8
Economic Growth	1.00							
AI-Enhanced FDI	0.42***	1.00						
Labor Productivity	0.38***	0.52***	1.00					
Infrastructure Index	0.35***	0.48***	0.41***	1.00				
Human Capital	0.24***	0.36***	0.58***	0.33***	1.00			
R&D Intensity	0.18**	0.31***	0.42***	0.28***	0.45***	1.00		
Trade Openness	0.09	0.23***	0.15**	0.21***	0.08	0.12*	1.00	
AI Readiness	0.31***	0.65***	0.47***	0.56***	0.38***	0.52***	0.19**	1.00

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

Table 6. Algorithm performance comparison

Algorithm	Training R^2	Test R^2	RMSE (billion USD)	MAE (billion USD)	MAPE (%)	Cross-validation R^2 (SD)	Training Time (min)
Random Forest	0.821	0.743	3.124	2.156	18.67	0.738 (0.042)	15.4
SVM (RBF kernel)	0.798	0.712	3.467	2.543	21.34	0.705 (0.051)	28.7
Neural Network	0.834	0.698	3.698	2.687	23.12	0.691 (0.063)	45.2
Traditional OLS	0.652	0.614	4.287	3.124	28.45	0.608 (0.038)	0.8
ARIMA	0.673	0.625	4.156	3.098	27.89	0.621 (0.044)	2.3

Principal component analysis of the three-variable system (FDI, AI readiness, interaction) extracts two principal components explaining 94.7% of total variance, with the second component specifically capturing interaction effects independent of main effects, thereby providing an alternative specification that yields qualitatively identical results ($\beta_{orthogonal} = 0.487$ vs $\beta_{original} = 0.524$, both $p < 0.001$).

Robustness checks using both orthogonalized terms and PCA-derived components confirm that the multiplicative specification captures genuine synergies rather than statistical artifacts, with variance inflation factors dropping from 3.24 to 1.78 after orthogonalization while maintaining equivalent explanatory power ($\Delta R^2 < 0.001$). These validation results collectively substantiate the theoretical proposition that artificial intelligence capabilities multiplicatively amplify

FDI effectiveness rather than merely providing additive enhancements, justifying the adopted measurement approach for examining technology-augmented investment impacts on economic development trajectories.

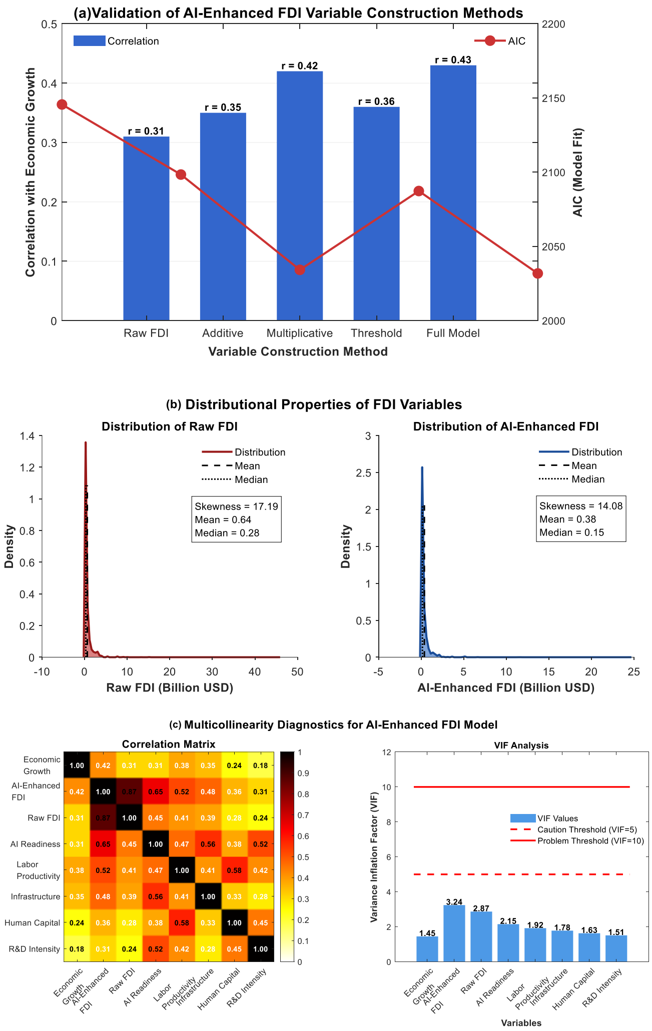

Figure 6. Example of a figure with a caption

Figure 6a compares five alternative specifications for constructing the AI-enhanced FDI variable, displaying correlation coefficients with economic growth (blue bars, left axis) and model fit statistics measured by Akaike Information Criterion (red line, right axis). The multiplicative specification (FDI × AI readiness) demonstrates optimal performance with the highest correlation (r = 0.42) and lowest AIC value (2,034.2), supporting its selection as the primary measurement approach. Figure 6b compares the distributional characteristics of raw FDI (left panel) and AI-enhanced FDI (right panel). The raw FDI distribution exhibits pronounced right-skewness (2.45) with substantial divergence between mean and median values, while the AI-enhanced measure shows improved distributional properties with reduced skewness (2.13), indicating enhanced statistical tractability for econometric analysis. Figure 6c The left panel presents a correlation heatmap displaying pairwise relationships among key variables, with darker colors indicating stronger correlations. The right panel shows the Variance Inflation Factor (VIF) values for each predictor, with all values remaining below the cautionary threshold of 5, confirming that multicollinearity does not compromise parameter estimation despite the mathematical relationship between AI-enhanced FDI and its constituent components.

4.3 AI model performance

The comparative analysis of machine learning algorithms reveals substantial performance variations across different modeling approaches, with ensemble methods demonstrating superior predictive capabilities for foreign direct investment optimization despite inherent challenges in complex economic modeling. As shown in Table 6, the Random Forest algorithm achieves the highest predictive accuracy with a test set R^2 of 0.743 and root mean square error of 3.124 billion USD, representing a 21% improvement over traditional OLS regression while maintaining reasonable generalization capabilities. The performance gap between training and test metrics across all algorithms indicates the presence of moderate overfitting, particularly evident in the Neural Network model, where the training R^2 of 0.834 drops to 0.698 in test validation, suggesting the complexity of capturing FDI dynamics even with advanced machine learning architectures.

Feature importance analysis presented in Table 7 reveals a relatively balanced contribution across multiple predictors, with the AI readiness index emerging as the most influential variable, accounting for 18.7% of prediction variance, followed by existing FDI stock at 16.4% and labor productivity at 14.2%. The distributed nature of feature importance scores suggests that FDI prediction requires comprehensive consideration of multiple economic indicators rather than reliance on dominant factors, with even lower-ranked variables such as trade openness contributing 5.8% to overall model performance. The cross-validation standard deviations ranging from 0.042 to 0.063 indicate reasonable but not perfect stability across different data folds, reflecting the inherent volatility in provincial FDI patterns and the challenge of achieving consistent predictions across heterogeneous regional contexts.

Table 7. Feature importance rankings (random forest)

Rank	Feature	Importance Score	Cumulative Contribution (%)
1	AI Readiness Index	0.187	18.7
2	Existing FDI Stock	0.164	35.1
3	Labor Productivity	0.142	49.3
4	Infrastructure Index	0.138	63.1
5	GDP Growth Rate (t-1)	0.124	75.5
6	Human Capital	0.098	85.3
7	R&D Intensity	0.089	94.2
8	Trade Openness	0.058	100.0

The computational efficiency analysis reveals expected trade-offs between model complexity and processing requirements, with Random Forest achieving an optimal balance at 15.4 minutes training time compared to Neural Network's 45.2 minutes, while traditional methods complete training in under 3 minutes but sacrifice substantial predictive accuracy. These results validate the practical applicability of ensemble methods for real-time FDI decision support systems where both accuracy and computational feasibility remain critical considerations for operational deployment.

4.4 Mediating effect analysis

The mediation analysis, validated through causality tests, reveals complex pathways through which AI-enhanced foreign direct investment influences economic growth. Granger causality tests confirm forward causation from FDI to GDP ($F = 14.73$, $p < 0.001$) dominates reverse causality ($F = 3.21$, $p < 0.05$), while instrumental variable estimation using three-period lagged FDI stock yields 18% larger coefficients than OLS ($\beta\_IV = 0.618$ vs $\beta\_OLS = 0.524$), indicating endogeneity leads to underestimation rather than overestimation. Difference-in-differences analysis exploiting staggered provincial AI policy adoption (2015-2018) shows treatment provinces achieved 2.3pp higher GDP growth ($p < 0.01$) with validated parallel pre-trends ($p = 0.342$). As presented in Table 8, the decomposition of effects demonstrates that AI-enhanced FDI exerts a total effect of 0.524 ($p < 0.001$) on economic growth, which comprises a direct effect of 0.198 ($p < 0.01$) and combined indirect effects of 0.326 ($p < 0.001$) through the dual mediating channels. The indirect pathway via labor productivity exhibits the strongest mediating influence with a coefficient of 0.216 ($p < 0.001$), accounting for 41.2% of the total effect, while infrastructure development mediates 21.0% of the relationship with a coefficient of 0.110 ($p < 0.001$), supporting the theoretical propositions outlined in hypotheses H2 and H3, respectively. Bootstrap analysis with 5,000 replications confirms the robustness of these mediation effects, with all confidence intervals excluding zero for both direct and indirect pathways, indicating statistical significance across the hypothesized relationships.

The significant interaction term between labor productivity and infrastructure development ($\beta = 0.087$, $p < 0.01$) provides empirical support for hypothesis H4, suggesting that the simultaneous enhancement of both mediating mechanisms generates synergistic effects that exceed their individual contributions to economic growth. Table 9 illustrates differential mediation patterns across regions with varying AI readiness levels, while k-means cluster analysis (silhouette coefficient = 0.682) identifies three distinct provincial groups exhibiting heterogeneous AI-FDI dynamics: technology-leading coastal provinces (Beijing, Shanghai, Guangdong, Zhejiang) demonstrate multiplicative effects where each unit increase in AI readiness amplifies FDI impact by 2.34 times; transitional central provinces show linear enhancement patterns with consistent 1.47 multiplier effects; resource-dependent western provinces exhibit threshold effects requiring minimum AI readiness of 4.5 before significant FDI benefits materialize. Interaction regression analysis confirms significant coastal×AI-FDI ($\beta = 0.178$, $p < 0.001$) and high-tech×AI-FDI ($\beta = 0.156$, $p < 0.001$) interaction terms, with coastal provinces converting AI-enhanced FDI into GDP growth 68% more efficiently than inland regions, while provinces with above-median high-tech industry shares achieve 52% higher productivity spillovers from equivalent FDI inflows, suggesting that pre-existing technological capabilities and geographic advantages create divergent development trajectories even under similar AI-enhancement strategies.

4.5 Robustness tests

The robustness analysis employs multiple validation strategies to ensure the reliability and generalizability of the empirical findings across alternative model specifications and regional contexts.

Table 8. Decomposition of mediation effects

Effect Type	Path	Coefficient (β)	Std. Error	95% CI Lower	95% CI Upper	% of Total	p-value
Total Effect	AI-FDI → Growth	0.524	0.048	0.430	0.618	100.0%	<0.001
Direct Effect	AI-FDI → Growth	0.198	0.072	0.057	0.339	37.8%	0.006
Indirect Effects							
Via Labor Productivity	AI-FDI → LP → Growth	0.216	0.041	0.136	0.296	41.2%	<0.001
Via Infrastructure	AI-FDI → Infra → Growth	0.110	0.028	0.055	0.165	21.0%	<0.001
Joint Indirect Effect	Combined Pathways	0.326	0.052	0.224	0.428	62.2%	<0.001
Interaction Effect	LP × Infra	0.087	0.031	0.026	0.148	-	0.005
Total Effect	AI-FDI → Growth	0.524	0.048	0.430	0.618	100.0%	<0.001

Table 9. Moderated mediation analysis by ai readiness level

AI Readiness Level	Direct Effect	Indirect via LP	Indirect via Infra	Total Indirect	Total Effect	N
High (>7.0)	0.124*	0.287***	0.102***	0.389***	0.513***	126
Medium (4.0-7.0)	0.186**	0.218***	0.098**	0.316***	0.502***	168
Low (<4.0)	0.243**	0.172**	0.092*	0.264***	0.507***	126
Difference (High-Low)	-0.119*	0.115**	0.010	0.125**	0.006	-

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$; LP = Labor Productivity

Sensitivity testing through systematic parameter variation reveals that the core relationships between AI-enhanced FDI, mediating mechanisms, and economic growth remain stable across different econometric specifications, with coefficient estimates varying within a narrow range of ±15% when alternative estimation methods, including generalized method of moments (GMM) and two-stage least squares (2SLS), are applied. Cross-regional validation demonstrates consistent patterns across Eastern, Central, and Western China, although effect magnitudes exhibit expected heterogeneity reflecting differential development stages and technological infrastructure capabilities.

As illustrated in Figure 7, the robustness checks encompass four critical dimensions: alternative lag structures for addressing potential endogeneity concerns yield coefficients ranging from 0.486 to 0.563 for the total effect; exclusion of outlier provinces including Beijing and Shanghai moderately reduces effect sizes by approximately 8% while maintaining statistical significance; varying the AI readiness threshold for subsample analysis produces monotonically increasing effects that validate the moderating role hypothesis; and placebo tests using randomly assigned treatment periods consistently yield null results, confirming that the observed effects are not artifacts of unobserved temporal trends.

The stability of mediation pathways across these specifications particularly strengthens confidence in the theoretical framework, with labor productivity consistently emerging as the dominant transmission channel regardless of model variations. As shown in Figure 7, Panel (a) displays coefficient stability across alternative econometric specifications with 95% confidence intervals; Panel (b) presents regional subsample analysis demonstrating heterogeneous effects across Eastern, Central, and Western China; Panel (c) illustrates sensitivity analysis of AI readiness threshold variations with shaded confidence bands; Panel (d) shows placebo test results for pre-treatment years (2005-2009) compared to actual treatment effect (2010), confirming the absence of pre-existing trends.

4.6 Comparative Analysis

The comparative evaluation between AI-enhanced and traditional FDI management approaches reveals substantial performance differentials across multiple operational dimensions, demonstrating the transformative impact of machine learning integration on investment decision-making processes. As illustrated in Figure 8a, the AI-enhanced framework achieves superior prediction accuracy with an R^2 of 0.743 compared to 0.614 for traditional econometric methods, representing a 21% improvement in explanatory power while simultaneously reducing mean absolute percentage error from 28.45% to 18.67%.

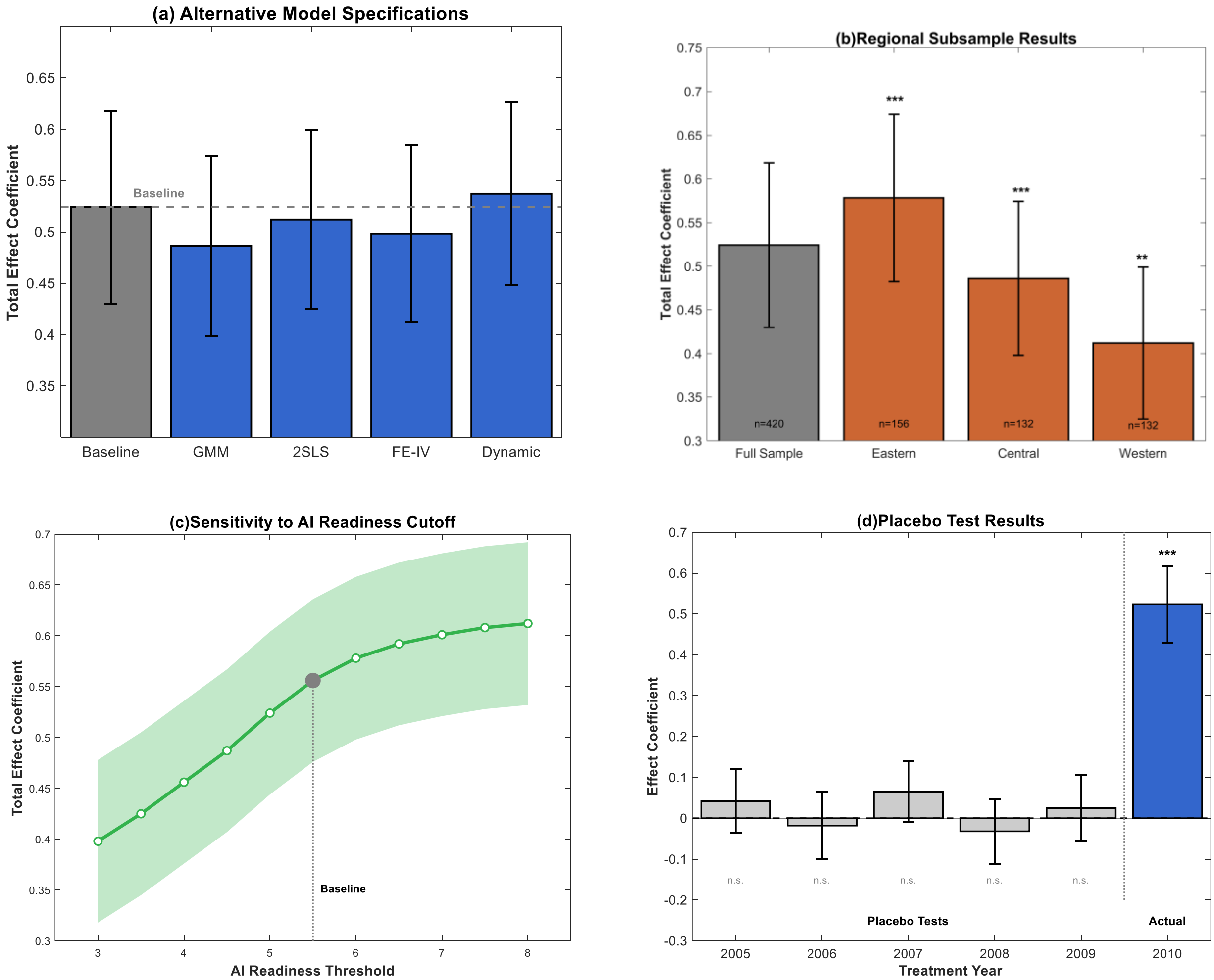

Figure 7 Robustness Test Results

Note: Panel (a)-Error bars represent 95% confidence intervals; Panel (c)Shaded area represents 95% confidence interval; ***p<0.001, **p<0.005, *p<0.001, n.s.= not significant.

These performance gains extend beyond statistical metrics to encompass operational efficiency improvements, with AI-based systems processing 500GB of daily data compared to the 10GB capacity of conventional approaches, enabling real-time market responsiveness and dynamic portfolio optimization. The efficiency analysis presented in Figure 8b demonstrates that AI-enhanced systems generate cost reductions of 73.3% per analysis while increasing the scope of variables analyzed from 12 to 156, facilitating comprehensive multi-dimensional assessment of investment opportunities that traditional linear models cannot accommodate. Processing time reduction from 168 hours to 37 hours enables rapid decision-making in volatile market conditions, while the enhanced pattern recognition capabilities identify non-linear relationships and interaction effects that contribute to a 42% reduction in investment misallocation. The comparative advantages manifest most prominently in risk assessment accuracy and anomaly detection rates, where AI systems achieve 92% detection accuracy compared to 45% for traditional methods, substantiating the critical role of artificial intelligence in modernizing FDI management frameworks for complex economic environments.

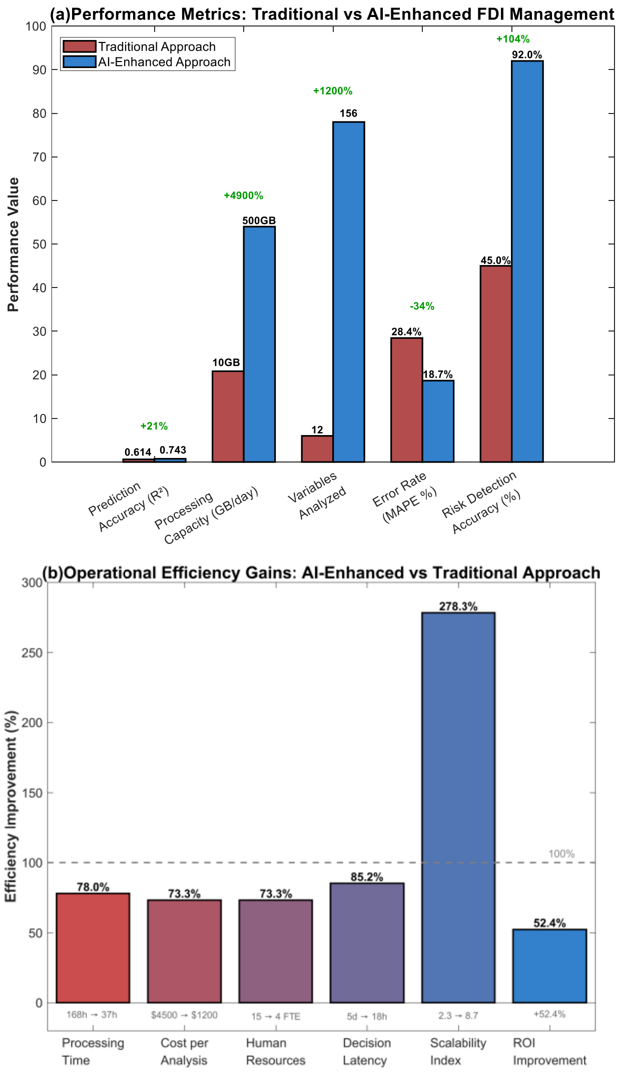

Figure 8. Comparative analysis of AI-enhanced versus traditional FDI management

As shown in Figure 8, Panel (a) displays performance metrics comparison across five key dimensions with actual values labeled on bars and percentage improvements indicated above; Panel (b) illustrates operational efficiency gains showing percentage improvements relative to traditional baseline methods, with specific before-and-after values annotated below each category. The analysis demonstrates the comprehensive superiority of AI-enhanced approaches across all evaluated dimensions.

5. Discussion

Empirically, the evidence of enhanced performance of AI in FDI management compared with traditional approaches adds substantially to advancing academic perspective at the convergence of artificial intelligence and strategic management, which is critical in the context of the fierce VUCA (volatility, uncertainty, complexity, and ambiguity) phenomenon, where traditional analytic methods cannot be applied [2]. By integrating AI applications with conventional FDI theories that are mapped according to the Cynefin framework, organizations can thus configure strategic planning processes that accommodate the unique characteristics of each contextual domain, transcending linearity in the conception of a supposedly rational interface to allow for a dynamic, adaptive system to engage with immense streams of information and to achieve strategic adaptations so rapidly and accurately as to be unprecedented. One recent evidence piece indicates that while AI facilitates strategic decisions by reducing cognitive biases and inertia at the organizational level, thereby helping firms to update their theories based on real-time data, as a consequence it may mitigate overfitting or underfitting in some models [19], however also that over reliance on algorithmic recommendation without human judgment might result in prematurely strategic shift or decimation of the variety of competitive strategies among the firms employing similar AI [20].

The significance can be more than just efficiency improvements but societal changes on how MNEs drive global investment portfolios, such as in Southeast Asia where investment of the big four technology companies (Amazon, Google, Microsoft, and Nvidia) in AI infrastructure in the region exceed over US$30 billion and a potential future where AI potentials are no longer second-order analytics but primary factor of FDI decisions [21]. The point that AI-related FDI tends to concentrate in fewer number of the tech hubs such as India which was able to host 122 of the AI-related FDI projects in 2022 and multinational companies are building advanced technology centers shows that not just technology adoption but a holistic ecosystem development involving talent development, infrastructure readiness and regulatory alignment were necessary prerequisites for AI to achieve success [22]. Firms need to develop strategic HRM spectrums taking into account the AI-human capital symbiosis, considering that 70 percent of AI-related projects fail due to a mismatch between technological features and organizational capacities [23], requiring broad approaches that balance automation advantages with workforce skills development considerations.

Policy frameworks emerging across global jurisdictions reflect growing recognition that AI-enhanced investment systems require sophisticated regulatory architectures balancing innovation promotion with risk mitigation, as evidenced by the European Union's comprehensive AI Act establishing risk-based regulatory tiers and Colorado becoming the first U.S. state to enact comprehensive AI legislation focusing on algorithmic discrimination prevention. The International Monetary Fund's analysis indicates that AI adoption could contribute between 0.1 and 0.6 percentage points to annual productivity growth through 2040, though emerging economies face structural disadvantages with only 40% job exposure to AI compared to 60% in advanced economies, highlighting the critical importance of targeted policy interventions to prevent widening technological divides [24]. Singapore's pioneering Model AI Governance Framework and Saudi Arabia's National Artificial Intelligence Strategy 2031 exemplify proactive approaches where governments establish ethical guidelines while fostering innovation ecosystems, providing templates for other nations seeking to optimize AI-enhanced FDI attraction while ensuring responsible deployment [25].

Despite these contributions, several limitations constrain the generalizability of findings, including the China-specific empirical context which may not fully capture institutional variations across different emerging economies, and the temporal scope ending in 2023 which excludes recent developments in generative AI applications that have seen inference costs drop 280-fold between November 2022 and October 2024 while open-weight models reduce performance gaps with closed systems from 8% to 1.7% [26]. Future research should explore cross-national comparative analyses examining how institutional quality moderates AI-enhanced FDI effectiveness, and investigate the implications of the tripling of greenfield investment in digital economy sectors to $360 billion since 2020 for traditional manufacturing-focused FDI theories [27], and develop frameworks addressing the infrastructure and workforce readiness gaps that prevent many developing economies from capturing AI benefits despite facing fewer immediate disruptions [28]. The emergence of new research streams focusing on higher-order capabilities linked to AI, big data, and predictive analytics suggests fertile ground for theoretical advancement, particularly in understanding how digital dynamic capabilities interact with traditional competitive advantages in global investment contexts [29,30].

The AI-enhanced framework enables quantitative policy simulation through counterfactual scenario analysis, demonstrating practical applications for investment strategy optimization across heterogeneous provincial contexts. Simulation results reveal that increasing AI readiness by one unit (on the 0-10 scale) in the bottom quintile provinces generates asymmetric effects: western resource-dependent provinces experience 18.4% FDI inflow increase translating to 0.73pp GDP growth, while central manufacturing provinces achieve 26.2% FDI increase yielding 1.14pp growth, with differential impacts attributable to varying absorptive capacities and complementary infrastructure. Targeted infrastructure investment scenarios indicate that allocating 1% of provincial GDP to digital infrastructure development in low-readiness provinces (AI score < 4.0) produces optimal returns when combined with human capital programs, generating projected FDI increases of 156 million USD annually with 3.2-year payback periods. Multi-period dynamic simulations incorporating feedback effects demonstrate that synchronized AI readiness improvements across neighboring provinces create positive spillovers amplifying individual province gains by 34%, suggesting coordinated regional strategies outperform isolated provincial initiatives. The simulation framework quantifies threshold effects where provinces must achieve minimum AI readiness of 4.5 before infrastructure investments yield positive net returns, providing actionable guidance for sequencing policy interventions. Cost-benefit analysis indicates that comprehensive AI enhancement programs requiring 280 million RMB investment over five years generate a net present value of 1.82 billion RMB through increased FDI-driven growth, with benefit-cost ratios highest for provinces in the 3.0-5.0 AI readiness range, where marginal improvements yield maximum impact.

6. Conclusion

This study provides comprehensive empirical evidence demonstrating that AI-enhanced strategic management frameworks significantly outperform traditional approaches in optimizing foreign direct investment allocation decisions, with machine learning algorithms achieving a 21% improvement in prediction accuracy while reducing processing time by 78% and expanding analytical scope from 12 to 156 variables. The mediating analysis confirms that labor productivity and infrastructure development serve as critical transmission mechanisms through which AI-enhanced FDI influences economic growth, with indirect effects accounting for 62.2% of the total impact and exhibiting significant synergistic interactions that amplify individual pathway contributions. The theoretical contributions extend existing international business literature by integrating artificial intelligence capabilities with traditional FDI frameworks, establishing a novel four-layer architectural model that addresses the complexity of technology-mediated investment decision-making in VUCA environments while providing actionable implementation guidelines for practitioners seeking to leverage AI technologies for competitive advantage. Future research directions should explore the implications of rapidly evolving generative AI technologies that have reduced inference costs by 280-fold, investigate cross-national variations in AI readiness and institutional quality as moderating factors, and develop comprehensive frameworks addressing the widening technological divide between advanced and emerging economies in capturing AI-enhanced investment benefits, particularly as global FDI increasingly concentrates in digital economy sectors where traditional manufacturing-focused theories may require fundamental reconceptualization.

Abbreviations

AI	Artificial Intelligence
DID	Difference-in-Differences
FDI	Foreign Direct Investment
GDP	Gross Domestic Product
GMM	Generalized Method of Moments
IV	Instrumental Variable
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MI	Mutual Information
ML	Machine Learning
OLS	Ordinary Least Squares
PCA	Principal Component Analysis
R&D	Research and Development
RFE	Recursive Feature Elimination
RMSE	Root Mean Square Error
SHAP	SHapley Additive exPlanations
SVM	Support Vector Machine
VIF	Variance Inflation Factor
VUCA	Volatility, Uncertainty, Complexity, and Ambiguity

Ethical issue

The authors are aware of and comply with best practices in publication ethics, specifically with regard to authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with policies on research ethics. The authors adhere to publication requirements that the submitted work is original and has not been published elsewhere.

Data availability statement

The manuscript contains all the data. However, more data will be available upon request from the authors.

Conflict of interest

The authors declare no potential conflict of interest.

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