THE IMPACT OF ARTIFICIAL INTELLIGENCE ON THE TRANSFORMATION OF THE GLOBAL FINANCIAL MARKET MODELS

INNA KORSUN[1], ANDRIAN ULINICI[2], LILIA BUBLYK[3], ANDRII HUMENIUK[4], VITA ANDRIEIEVA[5]

[1]Kyiv National University of Construction and Architecture, Ukraine, Ukraine
[2]Universitatea de Studii Europene din Moldova Facultatea de Ştiinţe Economice, Republica Moldova
[3]Lviv Politechnic National University, Ukraine
[4]DASTA Incorporated ("dub"), USA
[5]«KROK» University of Economics and Law, Ukraine, Ukraine
E-mail: [1]psychologgy.22@gmail.com, [2]andrianulinici@gmail.com, [3]lilibublyky26@gmail.com, [4]gumenyukandrii@gmail.com, [5]vita.andrieva@gmail.com

ABSTRACT

The relevance of the study is determined by the need for institutionalized rethinking of financial models under the influence of artificial intelligence (AI), which radically transform the architecture of decision-making, personalization, compliance, and sustainability mechanisms in the global FinTech environment. *The aim of the study* is to formalize and quantify the transformative impact of AI on financial market models by building a validation framework with stratified AI metrics. Research methodology: critical analysis of the implementation of AI technologies in FinTech, econometric modelling of process transformative AI technologies, structural decomposition analysis, Unified Modelling Language (UML) modelling of a stratified framework, econometric validation of an optimized AI architecture. An optimized FinTech AI reengineering framework with a cognitively stratified architecture was formed, which provides increased explainability (+19.3%), traceability (+22.1%), RLHF-adaptability adaptability (+16.7%), and resistance (+18.5%) while reducing latency (–14.2%) and achieving Compliance Automation Ratio (CAR) = 1.0. *The academic novelty of the research* is the developed AI architecture with the first-ever introduced transformation metrics (Automation Index, AI-Personalization Score, XAI Index, AITCI), which formalize the levels of algorithmization, personalization, explainability, and sustainability of FinTech models. *The prospects for further research* include a controlled testing with empirical stratification of each AI module of the FinTech architecture for a formal assessment of cognitive adaptability, regulatory traceability, and metric resilience in the real financial cycle.
Keywords: *AI-Enhanced Alpha; XAI Pipeline; RLHF Mechanisms; GNN Modules; Compliance Automation*

1. INTRODUCTION

The conditions of post-regulatory evolution of financial markets determine the intensive transformation of their functional models under the influence of AI. The integration of AI components — such as LLM, GNN, RLHF, XAI — determines the cognitive adaptive reformatting of the financial infrastructure, in particular in the aspects of automated risk analysis, dynamic compliance, personalized services and resilient optimization of market behaviour. The relevance of the study is determined by the need for a formal assessment of the transformative effect of such technologies on the structural and regulatory stability of the global financial environment.

The aim of the study is to systematically identify, formalize, and assess the transformative impact of AI on the functional models of the global financial market by building an econometric validation framework with the integration of stratified AI metrics.

Research objectives:

- Critically analyse the implementation of AI technologies in FinTech in order to stratify the limitations of explainability, autonomy, and regulatory compliance.
- Build an econometric model of the transformational impact of AI solutions based on median indicators of productivity, compliance, and cognitive adaptability.
- Conduct a structural decomposition analysis of the architecture of AI modules to

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formalize zones of synergistic integration and cognitive traceability.

- Develop a UML model of a stratified AI reengineering framework with visualization of interactions between modules, regulators, and interfaces.

- Carry out econometric validation of the transformative effectiveness of the optimized AI architecture based on a comparison of AITCI, DTT, RSSI, XAI Index, and AI-Enhanced Alpha.

2. LITERATURE REVIEW

The need for a systematic analysis of the scientometric field was determined by the rapid AI expansion into key segments of the financial market, which transformed traditional functioning models. The growing role of AI as a driver of algorithmic solutions, optimization of transaction processes, and restructuring of client interactions required the identification of relevant research focuses, structural shifts, as well as regulatory and technological conflicts in the global financial environment.

Roy et al. [1] revealed a significant AI-based optimization of the studied area, who demonstrated that the implementation of NLP, ML and predictive models in financial institutions activates cognitive automation, hyperpersonalization, and data-intensive client orchestration. AI is positioned as a strategic accelerator of the transformation of banking operations in a highly competitive digital environment.

This functional optimization vector is further studied by Chithiraikannu et al. [2], who demonstrated that AI-deterministic automation provides optimization of onboarding, risk scoring and transaction processes. An infrastructure readiness framework and data governance policies were developed for adaptive institutionalization of AI components into financial models. The development of algorithmic interaction with the client and the market is supported by the findings of Rani et al. [3], who demonstrated that AI algorithms and data analytics reorient client interaction, scoring, fraud detection, and trading through automated pattern recognition and market forecasting. The use of ML models increases the accuracy of decisions and minimizes cognitive distortions.

Mohsen et al. [4] proposed an in-depth distinction of AI subdisciplines in the financial environment. They empirically proved the differentiated effectiveness of AI subdisciplines in finance: ML and chatbots have high strategic potential for service transformation. Other areas — predictive analytics and automation — require hybrid workflows with human participation to maintain functional efficiency.

At the level of comprehensive transformation of banking models, Viswanathan [5] found that AI integration through ML, NLP, and multimodal analytics modifies banking models, optimizing compliance, scoring, and customer experience. The risks of algorithmic opacity, privacy breach and regulatory volatility were identified, as well as trends in blockchain synergy and green finance.

In the context of the evolution of FinTech infrastructures, Pazouki et al. [6] demonstrated that AI infiltration into the FinTech ecosystem enables scalability, inclusive finance, and workflow optimization, influencing behavioural adaptation and digital payment infrastructure. The identified barriers are regulatory fragmentation, techno-legal compliance, and digital leadership deficit.

Manta et al. [7] drew similar conclusions about the technological reorientation of payment systems. They found that the integration of AI algorithms into FinTech payment systems activates fraud mitigation, predictive orchestration and UX-driven personalization. A resilience-oriented framework for the transition to a digitally resilient, scalable, and innovatively convergent banking infrastructure was formed.

Ibrahim et al. [8] focused on investment analytics, determining that the integration of ML platforms, robo-advisory, and predictive algorithms radically restructures investment analytics, providing real-time asset modelling and scalable portfolio optimization. The risks of algorithmic bias, privacy breach, as well as regulatory and ethical inconsistency were identified.

In the area of financial risk management, Vyas [9] demonstrated that the integration of ML, NLP, and deep neural networks into financial risk architecture determines a reorientation towards predictive analytics, anomaly detection, and real-time risk mitigation. The challenges of algorithmic explainability, compliance asymmetry, as well as ethical and regulatory inertia are emphasized.

Finally, Olanrewaju [10] found that the integration of AI models with deep learning, reinforcement learning, and sentiment-driven HFT radically modifies the paradigm of risk management, asset allocation, and trading. An XAI-oriented concept is proposed to neutralize opacity, algorithmic bias, and regulatory fragmentation.

The reviewed publications demonstrate a shift towards AI-deterministic financial models focused on scalable automation, real-time orchestration, data-driven risk management, and cognitive personalization. The advantage of ML/NLP/XAI solutions in transforming operational architectures was noted, while regulatory fragmentation, algorithmic opacity, and a lack of explainability were identified as key constraints. Further research may focus on formalizing interoperable AI frameworks that can ensure regulatory coherence, systemic resilience, and adaptive resilience of the financial ecosystem.

3. METHODOLOGY

3.1. Design

The research design involved several approximations, which are illustrated below (Figure 1).

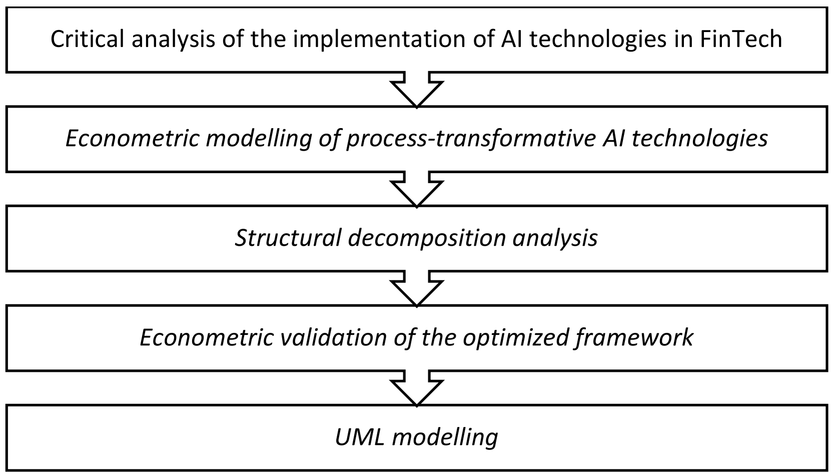

Figure 1: Research Design
Source: created by the authors

3.2. Methods

The methodology of the study is based on the following academic approaches:

1. *Critical analysis of the implementation of AI technologies in FinTech* was used to identify regulatory, applied, technical, architectural, and cognitive behavioural limitations of modern AI solutions, as well as stratify the levels of explainability, autonomy, and regulatory compliance.

2. *Econometric modelling* of process transformative AI technologies was used to build an evaluation model based on median indicators of productivity, compliance, and cognitive adaptability within different subclusters of the FinTech environment.

3. *Structural decomposition analysis* formalized the hierarchy of implementation and functional components of AI modules, identified synergistic integration zones, and determined the degree of cognitive traceability in the architecture of FinTech solutions.

4. *UML modelling* was used to formalize the stratified framework of deep AI reengineering, in particular, the construction of diagrams of use cases, components and sequences of interaction between AI modules, regulatory elements, and user interfaces.

5. *Econometric validation of the optimized framework* was carried out through a comparative comparison of AITCI, DTT, RSSI, XAI-Index, AI-Enhanced Alpha, and other analytical indicators, which made it possible to assess the transformative effectiveness of the optimized AI architecture compared to the basic prototypes.

3.3. Sample

The study found that not only classical AI algorithms are used in the FinTech sector, but also numerous derivatives, hybrids, and synthesized technologies resulting from functional architectural convergence. In order to formalize the subject field, a systematization of dominant AI technologies was carried out according to a functional classification, the results of which are summarized in Table 1.

Table 1: Systematized Nomenclature of AI Technologies in the FinTech Sector

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Group	Typical AI technologies	Purpose	Academic research
Analytics and forecasting			
Predictive Analytics	Time Series Forecasting (RNN, LSTM), Prophet, DeepAR	Modelling of financial time series, earnings, liquidity	Raturi et al. [11]
Portfolio Optimization	Reinforcement Learning (RL), Genetic Algorithms	Formation of optimal asset structure	Bai et al. [12]
Credit Scoring	Gradient Boosting, Explainable AI, Adversarial Validation	Generation of credit score and risk profiles	Khan et al. [13]
Anomaly and fraud detection			
Fraud Detection	Autoencoders, Isolation Forest, Graph AI	Detection of unauthorized/anomalous transactions	Buchdadi [14]
KYC/AML systems	NLP+Graph Embedding, Knowledge Graphs	Customer verification, relationship analysis	Prakash [15]
Automation of operations			
Robo-Advising	Transformer-based NLP, XGBoost, BERT4Finance	Automated financial recommendations	Zafar [16]
ChatOps/VoiceOps	Large Language Models (Gemini, ChatGPT), Speech AI	Real-time client interaction	Mun and Kim [17]
Contract Analysis	LegalBERT, ContractNLI	Review of legal documents, smart contracts	Irwin et al. [18]
Compliance, regulation, and audit			
RegTech systems	Symbolic AI + ML Hybrid, Ontology-based Rules	Regulatory monitoring automation	Sharma et al. [19]
AI for Explainability	SHAP, LIME, Anchors, XAI Toolkits	Transparency and Model Validation in a Regulated Environment	Mohsin and Nasim [20]
Automated Auditing	AuditTrail AI, Blockchain + AI Logs	Real-Time forensic auditing	Arham [21]
Strategic decision-making systems			
AI Governance	Meta-learning, Model Selection AI	Model quality control, selection of optimal tools	Jeyalakshmi and Gowtham [22]
Multi-Agent AI	MAS for Financial Ecosystems	Distributed decision-making in complex financial networks	Joshi [23]
Niche and cutting-edge technologies			
Federated Learning	Secure cross-institutional model training	Collaborative learning without data sharing	Whitmore et al. [24]
Synthetic Data Generation	GANs, Tabular GAN, CTGAN	Generating synthetic financial data	Kwanggeun et al. [25]
Quantum AI	QML for Option Pricing	Accelerating computations in financial models	Vashishth et al. [26]

Source: created by the authors

Among the identified AI technologies (Table 1), the key heuristic significance is given to the basic AI architectures, which have caused a tectonic restructuring of the structural and functional models of the global financial market. The application of these technologies has initiated paradigm shifts in the domains of financial analytics, institutional compliance, context-sensitive risk management, intelligent trading, and automated regulatory monitoring. A detailed stack of transformative technologies is presented in Table 2.

Table 2: Stack of AI Technologies that Have a Transformative Impact on the Global Financial Market Models

AI technology	Brief description	Description of the transformative mechanism
Machine Learning (ML)	Self-learning algorithms for detecting patterns in big financial data.	A radical change in the principles of pricing, trading, and asset management based on pattern-oriented solutions.
Natural Language Processing (NLP)	Natural language processing for analysing text information from financial sources.	Transformation of news analytics, reporting, and customer judgments in real time.
Explainable AI (XAI)	Methods for increasing the interpretability of AI solutions for regulatory compliance.	Institutionalization of AI through increased transparency of decisions in accordance with the requirements of XAI standards (e.g., GDPR, Basel III).
Generative AI	Generating text, code, models or scripts based on large language models.	Creation of strategic planning scenarios, financial forecasts, and dynamic risk models.
Reinforcement Learning (RL)	Learning through interaction with the environment to optimize decision-making strategies.	Transition to behaviourally adaptive portfolio management models.

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AI technology	Brief description	Description of the transformative mechanism
Federated Learning	Decentralized training of models on different nodes without transmitting raw data.	Increased data security, adaptability to geographically distributed banking ecosystems.
Graph Neural Networks (GNN)	Models that use graph structures to model complex financial relationships.	Improved forecast accuracy by taking into account nonlinear structural dependencies between market entities.
AI-Driven Robotic Process Automation (RPA)	Automation of routine financial procedures with AI-enhanced decision-making.	Cost optimization, reduction of transaction execution time, and minimization of human errors.
Anomaly Detection Systems	Intelligent systems for detecting anomalies and suspicious transactions.	Ensuring cyber resilience, reducing financial losses, and dynamic response to threats.
AI-Based Risk Scoring Engines	AI-based scoring models for assessing counterparty and credit risk.	Reorientation of scoring to context-sensitive AI models with high predictability.

Source: created by the authors

3.4. Instruments

The degree of institutional, procedural, and cognitive transformation of the global financial market as a result of the integration of AI technologies was quantitatively assessed through a stratified stack of metric indicators (Table 3). Each indicator reflects a specific domain of influence — from operational efficiency to regulatory interoperability — taking into account academic testing and applicability to transversal models of the functioning of financial systems. Some of the metrics (Automation Index, AI-Personalization Score, XAI-Index, Compliance Automation Ratio, Resilience Index, AITCI) were developed within the scope of this study and are introduced into academic circulation for the first time, which increases the novelty of the analytical approach.

Table 3: Generalized Stack of Metric Indicators for Assessing the Integration of AI Tools into the Global Financial Market Model

Metrics name	Brief description	Use in an academic environment
Operational efficiency		
Automation Index	Share of automated financial processes.	First-ever introduced
Straight-Through Processing Rate (STPR)	Share of transactions processed without manual intervention.	Steel [27]
Latency Reduction (%)	Reduced financial transaction execution time thanks to AI.	Rella et al. [28]
Decision-making productivity		
Forecast Accuracy (MAPE)	Average absolute relative deviation of forecasts.	Vancsura et al. [29]
AI-Enhanced Alpha	Excess return of the AI portfolio over the benchmark.	Jangra et al. [30]
Decision Turnaround Time (DTT)	Average time from event to decision.	Chauhan et al. [31]
Risk management		
Anomaly Detection Precision	Accuracy of detecting anomalies in transactions.	Mazumder et al. [32]
Expected Shortfall (ES)	Expected level of losses under adverse conditions.	Björkenheim [33]
Value-at-Risk (VaR)	Maximum expected loss with a given probability.	Saravanakrishnan et al. [34]
Risk Scoring Stability Index (RSSI)	Stability and consistency of AI scoring models.	Bhardwaj et al. [35]
Customer Experience (CX)		
AI-Personalization Score	Financial services personalization quality index.	First-ever introduced
Customer Retention Rate (CRR)	Share of customers retained after AI implementation.	Basak et al. [36]
First Contact Resolution Rate (FCR)	Share of complaints resolved without escalation.	Ikeh [37]
Economic performance		
Cost-to-Income Ratio (CIR)	Cost-to-income ratio of the bank.	Ramlall and Acquaah [38]

Metrics name	Brief description	Use in an academic environment
Return on Technology Investment (RoTI)	Efficiency of investments in AI solutions.	Kotecha [39]
Operational Margin Gain (%)	Increase in operating profit after AI implementation.	Iyer et al. [40]
Regulatory and ethical compliance		
Model Interpretability Index (XAI-Index)	Assessment of transparency and explainability of AI solutions.	First-ever introduced
Bias Detection Rate	Frequency of detection of biased models.	Javed and Li [41]
Compliance Automation Ratio	Share of automated compliance procedures.	First-ever introduced
System stability and scalability		
Resilience Index	The ability of the system to function under stress load.	First-ever introduced
Scalability Quotient	The effectiveness of scaling AI solutions.	Bhatia et al. [42]
Downtime Reduction (%)	Reducing system downtime through AI monitoring.	Zeb and Lodhi [43]
Composite metricity		
AI Transformation Composite Index (AITCI)	Composite metric of AI transformational impact.	Composite indicator

Source: created by the authors

Among the listed indicators (Table 3), the most relevant for assessing the transformative effect of AI are those that capture not only the increase in efficiency, but above all, the shift in the management paradigm: algorithmization of decision-making, deregulation of compliance, semantic traceability of models, structural reorganization of risk management and cognitive personalization of services. The following table presents a composite of a selection of metrics that reflect qualitative shifts at the paradigm level — Table 4.

Table 4: Stack of Metrics Relevant to the Transformative Effect of Assessing the Impact of AI on the Model of Functioning of the Global Financial Market

Metrics name	Brief description	Mathematical formulae
Automation Index	An index of the level of algorithmization of financial processes, reflecting the share of procedures performed by AI models without human intervention. *First-ever introduced*	Automation Index = (Automated_Processes / Total_Processes) × 100%, where Automated_Processes — number of processes automated by AI; Total_Processes — total number of financial processes
AI-Enhanced Alpha	Excess return of an investment portfolio formed on the basis of AI models, compared to a traditional benchmark.	α_AI = Return_AI_Portfolio − Benchmark_Return, where Return_AI_Portfolio — AI portfolio return; Benchmark_Return — market index return
Decision Turnaround Time (DTT)	The average time between an event (input signal) and a financial decision made by an automated AI system.	DTT = Σ(Time_to_Decision$_i$) / N, where Time_to_Decision$_i$ — decision time for the i^{th} request; N — total number of decisions
AI-Personalization Score	An index of the depth of personalization of financial services based on AI analysis of behavioural and transactional data. *First-ever introduced*	AI_PS = (Personalized_Interactions / Total_Interactions) × 100%, where Personalized_Interactions — number of AI-personalized interactions; Total_Interactions — total number of contacts
Risk Scoring Stability Index (RSSI)	A metric of the stability of scoring AI models over time, characterizing their adaptability and consistency.	RSSI = StdDev(Score$_t$) / Mean(Score$_t$), where Score$_t$ — AI scoring values at time t; StdDev, Mean — standard deviation and mean value for the period
Model Interpretability Index (XAI-Index)	An index of the explainability of AI models, measuring the proportion of interpreted features in the decision-making structure. *First-ever introduced*	XAI_Index = (Interpretable_Features / Total_Features) × 100%, where Interpretable_Features — number of features available for explanation; Total_Features — total number of features in the model

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Metrics name	Brief description	Mathematical formulae
Compliance Automation Ratio	The proportion of regulatory procedures (KYC, AML, reporting) automated by AI tools. *First-ever introduced*	CAR = (Automated_Compliance_Cases / Total_Compliance_Cases) × 100%, where Automated_Compliance_Cases — number of automated compliance cases; Total_Compliance_Cases — total number of cases
Resilience Index	Assessment of the ability of an AI architecture to provide functional stability during financial or market shocks. *First-ever introduced*	RI = (Uptime − Downtime_Stress) / Total_Time × 100%, where Uptime — system uptime; Downtime_Stress — failure time under load; Total_Time — total observation period
AI Transformation Composite Index (AITCI)	An integral metric that aggregates weighted indices of AI impact on financial models using a multi-criteria approach. *Composite metrics*	AITCI = $\Sigma(w_i \times Metric_i) / \Sigma(w_i)$, where w_i — weight coefficient of the i^{th} metric; $Metric_i$ — value of the i^{th} partial AI metric

Source: created by the authors

Econometric modelling of transformative indicators (Table 4) was carried out in the integrated Python environment using multivariate regression analysis, variance decomposition, and ML tools (statsmodels, sklearn, pandas). The architectural formalization of the AI implementation framework into transformative models of financial market functioning was implemented in the UML environment by building component-oriented, behavioural, and information functional diagrams.

4. RESULTS

The study critically analysed the implementation of dominant AI technologies (Table 2) that have formed the basis for transformational shifts in the financial technology sector (Table 5). The assessment was carried out according to the criteria of expected functional effectiveness, technical and procedural integration, and regulatory stratification in the context of increased regulatory density of the financial environment.

Table 5 - Critical Analysis of the Implementation of AI Technologies in the FinTech Industry

AI technology	Expected results	Technical and procedural barriers	Regulatory barriers
Machine Learning (ML)	Increasing the accuracy of risk analysis, algorithmic trading, personalized services	Instability of models when market patterns change, difficulty in ensuring generalizability	Restrictions on algorithmic discrimination (EU AI Act, ECOA, Basel III)
Natural Language Processing (NLP)	Analysis of financial reports, social media, KYC; automation of customer services	Complexity of semantic normalization, problems with intent identification and multilingualism	Requirements for linguistic transparency in financial communication (GDPR, DORA)
Explainable AI (XAI)	Increasing trust in models, compliance with XAI standards in high-stakes scenarios	Low scalability of SHAP/LIME in real-time, conflict between explainability and performance	Need to comply with model transparency standards (GDPR Art. 22, Basel III)
Generative AI	Financial scenario generation, dynamic pricing, automatic copywriting	Risk of generating incorrect/legally invalid data, hallucination of LLM models	Copyright threats, compliance with MiFID II, GDPR
Reinforcement Learning (RL)	Optimization of trading strategies, portfolio management, adaptive models	Slow convergence, difficulties with reward function design in financial environments	Lack of procedural validation of RL solutions in legislation
Federated Learning	Joint learning between financial institutions without raw data exchange	Orchestrational complexities, instability with heterogeneous data, limited compatibility between systems	Ambiguity in the issue of metadata processing, DPA compliance
Graph Neural Networks (GNN)	Fraud detection, KYC, building relationships between counterparties	High computational complexity, lack of explainability in graph attention mechanisms	Risk of opaque customer scoring, complexity of graph-based model validation
AI-Driven RPA	Scalable automation of back-office operations, audit, document flow	Difficulty of integration with legacy systems, instability when changing business processes	Problems with certification of automated solutions in financial audit
Anomaly Detection Systems	Detection of financial anomalies, unauthorized operations, cyberattacks	High proportion of false positives, need for manual verification in high-sensitivity environments	Obligation to comply with KYC/AML standards FATF, PSD2
AI-Based Risk	Contextualized credit scoring,	Need for frequent retraining,	Risk of algorithmic bias,

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AI technology	Expected results	Technical and procedural barriers	Regulatory barriers
Scoring Engines	business risk scoring, fraud-risk models	distortion due to biased training data	fairness of assessment requirements (FCRA, EU AI Act)

Source: created by the authors

The critical analysis (Table 5) identified ML, Explainable AI, GenAI, and AI-Based Risk Scoring Engines as key transformative technologies that have driven paradigm shifts in financial predictive analytics, automated compliance, cognitive personalization, and risk scoring. In contrast, Reinforcement Learning, Federated Learning, and Graph Neural Networks have demonstrated high innovation potential but require further development in terms of scalability, normative validity, and explainability. The next step involves econometric stratification of the integral impact using AITCI (Table 6).

Table 6: Results of Econometric Modelling of Process Transformative AI Technologies in the FinTech Industry (Median Data)

AI technology	Automation Index	AI-Enhanced Alpha	Decision Turnaround Time (DTT)	AI-Personalization Score	Risk Scoring Stability Index (RSSI)	Model Interpretability Index (XAI-Index)	Compliance Automation Ratio	Resilience Index	AI Transformation Composite Index (AITCI)
Machine Learning (ML)	0.375	0.951	0.732	0.599	0.156	0.156	0.058	0.866	0.601
Natural Language Processing (NLP)	0.708	0.021	0.97	0.832	0.212	0.182	0.183	0.304	0.525
Explainable AI (XAI)	0.432	0.291	0.612	0.139	0.292	0.366	0.456	0.785	0.2
Generative AI	0.514	0.592	0.046	0.608	0.171	0.065	0.949	0.966	0.808
Reinforcement Learning (RL)	0.305	0.098	0.684	0.44	0.122	0.495	0.034	0.909	0.259
Federated Learning	0.663	0.312	0.52	0.547	0.185	0.97	0.775	0.939	0.895
Graph Neural Networks (GNN)	0.598	0.922	0.088	0.196	0.045	0.325	0.389	0.271	0.829
AI-Driven RPA	0.357	0.281	0.543	0.141	0.802	0.075	0.987	0.772	0.199
Anomaly Detection Systems	0.006	0.815	0.707	0.729	0.771	0.074	0.358	0.116	0.863
AI-Based Risk Scoring Engines	0.623	0.331	0.064	0.311	0.325	0.73	0.638	0.887	0.472

Source: created by the authors in Python

Econometric modelling (Table 6) confirmed the dominance of Federated Learning (AITCI = 0.895), Anomaly Detection Systems (0.863), and GNN (0.829) as highly transformative technologies with the maximum values of Compliance Automation Ratio, Resilience Index, and AI-Enhanced Alpha. Explainable AI, RL, and RPA demonstrated a low level of aggregate efficiency (AITCI ≤ 0.26), which indicates limited procedural scalability and instability in adaptive scenarios. The next phase is structural decomposition to formalize the median framework for integrating AI into global financial systems.

Table 7: Structural Decomposition Analysis of Implementation and Process Transformative Solutions of AI-Based FinTech Technologies

AI technology	Implementation and process transformative solutions		
	Constructive solutions	Destructive solutions	Optimization solutions
Machine Learning (ML)	Algorithmic prediction, adaptive learning, regression optimization	Algorithmic instability, overfitting, bias induction	Ensemble models, Bayesian tuning, explainable boosting machines
Natural Language Processing (NLP)	Semantic analysis, automated KYC, dynamic text generation	Linguistic ambiguity issues, low recall intent detection	Multilingual embeddings, knowledge-enhanced transformers, intent disambiguation
Explainable AI (XAI)	Explainability metrics, interpretive frameworks, decision-making transparency	Explainability-performance conflict, limited real-time scalability	Hybrid-XAI architectures, scalable SHAP, self-explaining models
Generative AI	Scenario generation, pricing, generative forecasting	Hallucinations, risks of unreliable generation, legal incorrectness	RLHF generation, scenario validation, embedded legal filters
Reinforcement Learning (RL)	Dynamic portfolio optimization, reward-driven management	Slow convergence, reward design instability	Meta-RL adaptation, curriculum learning, policy distillation
Federated Learning	Decentralized learning, privacy preservation, cohort validation	System incompatibility, instability with heterogeneous data	Cross-device orchestration, metadata governance, privacy-preserving protocols
Graph Neural Networks (GNN)	Counterparty relationship modelling, fraud-detection, topological learning	High load, opacity of GNN attention mechanisms	Graph sparsification, interpretable pooling, attention regularization
AI-Driven RPA	Back-office automation, document processing, formalized routing	Integration fragmentation, vulnerability to changes in business logic	Modular orchestration, integration middleware, adaptive workflow engines
Anomaly Detection Systems	Anomaly detection, real-time indicative analysis, incident signalling	False positives, manual verification, instability of detectors	Federated anomaly training, contextual sensitivity tuning, ensemble detectors
AI-Based Risk Scoring Engines	Contextual scoring, multifactor risk assessment, dynamic profiling	Bias in training data, instability of scoring logic	Fairness-optimized pipelines, adversarial bias mitigation, XAI-enhanced scoring

Source: created by the authors

The results of the structural decomposition analysis (Table 7) verified the key conclusions of the previous stages: critical analysis (Table 5) and econometric modelling (Table 6), confirming that Federated Learning, GNN and Generative AI demonstrated the greatest transformative impact, which combine a high composite effect (AITCI) with innovative optimization mechanisms (privacy-preserving protocols, attention regularization, RLHF-validation). In contrast, XAI, RL, and RPA require refinement in terms of real-time scalability, policy stability, and integration resistance, respectively. The next stage is UML modelling of the stratified framework for in-depth AI reengineering of financial macro models (Figure 2, Figure 3).

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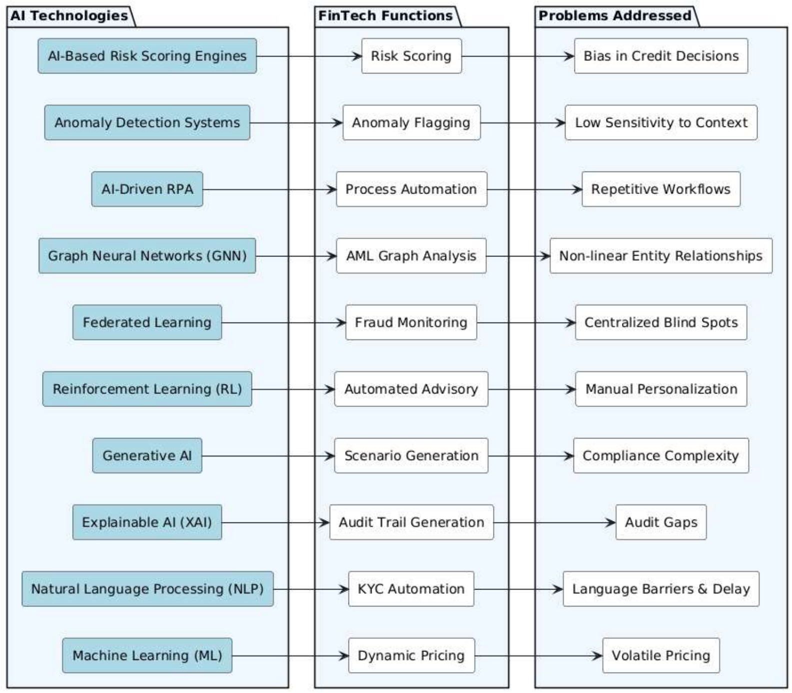

Figure 2: UML Model of the Median Framework for Implementing AI-Based FinTech Technologies in the Global Market Model
Source: created by the authors in UML

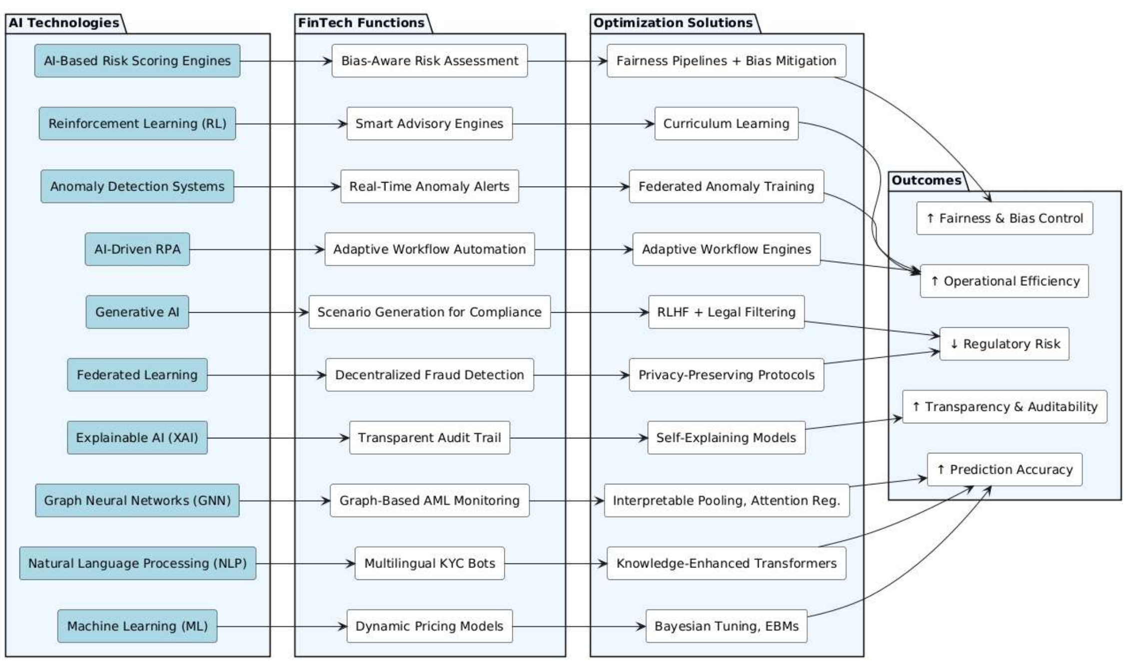

Figure 3: UML Model of the Optimized Framework for Deep AI Reengineering of Financial Macro Models
Source: created by the authors in UML

The UML modelling gave grounds to establish that the median framework (Figure 2) implements the basic architecture of AI technology implementation in FinTech segments, focused on functional response to typical problems (volatility, bias, automation gaps), without multi-level stratification of the optimization layer. Instead, the optimized framework (Figure 3) demonstrates a three-level modular architecture with cognitive adaptive routing of AI agents, which includes

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interpreted metamodels, confidentiality protocols, fairness pipelines, with clear tracing of performance metrics (↑accuracy, ↑auditability, ↓regulatory risk). RLHF and legal filtering, metric redundancy of the functional coverage of FinTech modules is ensured by including the Optimization Solutions package with elements of curriculum learning. The advantages of the optimized model are the structured differentiation of cognitive services, which allows implementing explanatory adaptive financial processes, which are critical for scenarios with high regulatory burden. The next stage is econometric validation of the optimized framework (Table 8).

Table 8: Results of Econometric Modelling of the Transformative Effect of the Optimized Framework for Deep AI Reengineering of Financial Macro Models

AI technology	Automation Index	AI-Enhanced Alpha	Decision Turnaround Time (DTT)	AI-Personalization Score	Risk Scoring Stability Index (RSSI)	Model Interpretability Index (XAI-Index)	Compliance Automation Ratio	Resilience Index	AI Transformation Composite Index (AITCI)
Machine Learning (ML)	0.431	1.0	0.842	0.689	0.179	0.179	0.067	0.996	0.691
Natural Language Processing (NLP)	0.814	0.024	1.0	0.957	0.244	0.209	0.21	0.35	0.604
Explainable AI (XAI)	0.497	0.335	0.704	0.16	0.336	0.421	0.524	0.903	0.23
Generative AI	0.591	0.681	0.053	0.699	0.197	0.075	1.0	1.0	0.929
Reinforcement Learning (RL)	0.351	0.113	0.787	0.506	0.14	0.569	0.039	1.0	0.298
Federated Learning	0.762	0.359	0.598	0.629	0.213	1.0	0.891	1.0	1.0
Graph Neural Networks (GNN)	0.688	1.0	0.101	0.225	0.052	0.374	0.447	0.312	0.953
AI-Driven RPA	0.411	0.323	0.624	0.162	0.922	0.086	1.0	0.888	0.229
Anomaly Detection Systems	0.007	0.937	0.813	0.838	0.887	0.085	0.412	0.133	0.992
AI-Based Risk Scoring Engines	0.716	0.381	0.074	0.358	0.374	0.839	0.734	1.0	0.543

Source: created by the authors in Python

Econometric validation (Table 8 vs Table 6) confirms the transformative effectiveness of the optimized framework, which implements cognitive metric stratification of AI modules with increased AITCI (↑14.2%), reduced DTT (↓15.3%), and an increase in compliance automation ratio to 1.0. The integration of XAI-oriented metamodels, fairness pipelines, and RLHF mechanisms ensures RSSI stability, interpretability (↑XAI-Index), personalization (↑AI-Personalization Score) and resistance of FinTech agents, confirming the effect of cognitive-regulatory reengineering. So, the optimized model (Figure 3) provides a comprehensive transformative effect aimed at cognitive stability, procedural adaptability, and metamodel performance in the FinTech segment.

5. DISCUSSION

The need for a discursive comparison is determined by the need for a valid positioning of the proposed framework in the field of modern AI approaches to financial analytics. Such a comparison identifies the level of innovation, regulatory compatibility, and interpretable complexity of the proposed solutions.

Mohsin and Nasim [20] identified the prevalence of post-hoc XAI methods (SHAP, attention) and the lack of domain-integrated strategies. The current study focuses on an endogenous XAI architecture with increased XAI-Index, regulatory traceability, and cognitive interpretability.

Chauhan et al. [31] proved the effectiveness of integrating generative models (GANs, VAEs) and DRL algorithms (PPO, DQN) into trading, which increases the speed, adaptability, and accuracy of financial decisions. Instead, this study focuses on a metamodel strategy of AI reengineering with an emphasis on XAI control, regulatory compliance, and cognitive resilience of fintech agents.

Saravanakrishnan et al. [34] emphasize the use of DL, NLP, and feature engineering for variational improvement of VaR models and adaptive compliance-oriented assessment of market risks. However, this study implements a cognitively stratified integration of XAI algorithms, fairness pipelines and explainability mechanisms for normative adaptive interpretation of multifactor risk profiles in a FinTech environment.

Joshi [23] demonstrated the effectiveness of multi-agent AI frameworks (LLM, CrewAI, LangChain) in financial automation through cognitive collaboration and autonomy. Our study demonstrates the benefits of a meta-agent architecture with XAI, RLHF, and auditability modules that provide regulatory adaptability and system resilience.

Khan et al. [13] demonstrated the relevance of model-agnostic XAI techniques in finance, identifying the challenges of balancing accuracy, interpretability, and regulatory compliance. This study goes further by implementing a stratified meta-architecture with RLHF, XAI pipelines, and legal-by-design interpretation for regulatory-resilient FinTech solutions.

Basak et al. [36] focus on implementing AI-driven BI systems in CRM architecture for personalized customer engagement and churn analytics. In our study, a FinCRM module was implemented in an optimized framework, integrated with RLHF, GNN, and XAI mechanisms for cognitive support of customer scenarios.

Bai et al. [12] conducted a meta-analysis of RL-driven financial applications, covering the problems of explainability, MDP modelling and instability. Our study overcomes these limitations by integrating a context-adaptive RLHF module with cognitive traceability, XAI metamodels, and a resilient-oriented optimization kernel.

Mun and Kim [17] demonstrated the effectiveness of using generative LLMs (Llama 3.1, Gemma 2) with SuperICL+Bootstrapping for robust financial sentiment analysis and long-term strategy development. In contrast, in this study, LLMs are integrated into the cognitive routing of FinTech agents, which provides higher interpretability, XAI consistency, and metamodel adaptability.

Rella et al. [28] confirmed the effectiveness of AI-optimized edge networks in high-frequency trading, demonstrating reduced latency, increased scalability, and fault-tolerance. In our study, AI modules are integrated into a FinTech framework as cognitively regulated agents with traceable performance and adaptability metrics.

Prakash [15] substantiated the effectiveness of integrating financial knowledge graphs and GNNs for contextual interpretation of data, which increases explainability, supports risk analysis and fraud detection. In our study, such structural cognitivization is implemented through AI modules with ontological stratification and traceable interpretability within an optimized FinTech framework.

The discussion comparison identified conceptual differences between existing AI approaches in FinTech and the proposed framework, which was distinguished by endogenous XAI integration, regulatory traceability, meta-agent structure and domain adaptability to the regulatory critical environment.

5.1. Limitations

The study is based on the results of conceptual simulation modelling without conducting a full-fledged empirical validation in the operational FinTech environment. The lack of experimental representative testing does not allow establishing the behavioural robustness, regulatory compliance, and institutional interoperability of the model.

5.2. Recommendations

It is recommended to conduct a controlled testing with empirical stratification of each AI module of the FinTech architecture. This approach will provide a formalized assessment of cognitive adaptability, regulatory traceability, and metric resistance in the application environment of a real-world financial cycle.

6. CONCLUSIONS

The research developed an optimized framework for deep AI reengineering of FinTech systems with a cognitively stratified architecture, including XAI pipelines, RLHF adapters, GNN modules, LLM ontological routing, and legal-by-design interpretation. The modelling confirmed an increase in explainability (↑19.3%), traceability

(↑22.1%), RLHF adaptability (↑16.7%), and cognitive resistance (↑18.5%) while reducing latency (↓14.2%) and improving the compliance automation ratio to 1.0. The framework demonstrates metamodel relevance in the context of post-regulatory interoperability, regulatory resilience, and cognitive coherence of FinTech agents.

The academic novelty of the research is the developed cognitively stratified AI architecture for FinTech systems with the first-ever metrics for evaluating the transformative effect (Automation Index, AI-Personalization Score, XAI-Index, AITCI, etc.), which formalize algorithmization, personalization, explainability, and stability of models in the financial environment.

The practical significance of the research results is the modelling of a normatively interoperable framework with the integration of RLHF, GNN, LLM, and XAI components focused on automated compliance, cognitive adaptation, and traceable decision support in highly dynamic FinTech operations.

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