

Article

FTAFO: A Federated Transparent Adaptive Financial Optimizer for Reducing Third-Party Dependencies in Workflow Management

Ziyi Wang ^{1,*} and Aixin Kang ²

¹ Enterprise Risk Management, Columbia University, NY, USA

² Master of Science in Quantitative Economics, Georgetown University, DC, USA

* Correspondence: Ziyi Wang, Enterprise Risk Management, Columbia University, NY, USA

Abstract: Modern financial institutions face increasing challenges due to opaque third-party AI systems governing critical workflow decisions. After firsthand experience with the limitations of existing solutions during a complex 18-month implementation project, we developed FTAFO (Federated Transparent Adaptive Financial Optimizer), a novel framework that fundamentally rethinks financial workflow optimization by introducing three core innovations: a federated consensus mechanism enabling distributed decision-making without reliance on centralized black-box systems, an adaptive transparency engine providing real-time explanations while maintaining computational efficiency, and a multi-objective optimization algorithm that simultaneously balances performance, interpretability, and regulatory compliance. Extensive testing across five financial institutions demonstrated promising results, with workflow processing times improving by approximately 18-28%, third-party licensing costs reduced by roughly 60-70%, and regulatory audit preparation time decreasing from several weeks to around 2-3 days. Implementation revealed challenges including initial setup complexity and the need for substantial staff retraining. Nevertheless, the framework's open architecture offers a practical alternative to vendor lock-in while meeting stringent regulatory requirements. This work contributes to the growing field of explainable AI in finance, though limitations remain in ultra-high-frequency scenarios and environments with restricted technical infrastructure.

Keywords: federated optimization; financial workflows; transparent AI; dependency reduction; regulatory compliance

Received: 08 October 2025

Revised: 25 October 2025

Accepted: 08 November 2025

Published: 13 November 2025



Copyright: © 2025 by the authors. Submitted for possible open access publication under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

The financial services industry's relationship with artificial intelligence has become increasingly complex [1]. During our initial research phase, spanning 18 months (Jan 2024-Jun 2025), we observed a troubling trend: major financial institutions were increasingly dependent on black-box AI solutions that, while effective, introduced substantial operational and regulatory risks.

This became evident during a particularly challenging consultation with a mid-sized bank struggling with its credit approval workflow [2]. Their existing system, provided by a major technology vendor, processed applications efficiently but could not explain the rationale behind specific decisions. When regulators requested detailed justifications for approval patterns, the bank was unable to provide meaningful explanations beyond stating that the AI system recommended the outcome.

1.1. The Growing Problem

Financial workflows now underpin modern banking operations, yet most institutions rely on proprietary systems that they neither fully understand nor control [3]. A preliminary survey of 47 financial institutions revealed that roughly 78% use third-party AI for critical decision-making, with average annual licensing costs exceeding \$2.3 million per institution.

The COVID-19 pandemic intensified these challenges [4]. Remote operations exposed the risks of dependence on external vendors for essential systems. We documented multiple cases in which vendor service disruptions caused significant operational delays, including one instance where a payment processing workflow was offline for nearly six hours due to a third-party AI service outage.

Regulatory pressures have further complicated the landscape. The European Union's AI Act, along with similar emerging frameworks, requires financial institutions to provide detailed explanations for AI-driven decisions. Traditional black-box systems struggle to meet these requirements, forcing institutions to choose between compliance and operational efficiency.

1.2. Our Research Journey

This paper arises from an 18-month research project that began with a fundamental question: Can AI systems be designed to match or surpass the performance of commercial solutions while providing full transparency and reducing vendor dependencies?

The journey was not straightforward. Early prototypes suffered from computational inefficiencies; the first transparent optimization engine was roughly 40% slower than commercial alternatives. Industry partners initially questioned whether the benefits of transparency justified potential performance losses.

The breakthrough occurred when we recognized that transparency could enhance, rather than hinder, optimization. By making decision processes visible, we were able to identify and correct inefficiencies that remained hidden in black-box systems. This insight led to the development of FTAFO.

1.3. Key Contributions

This research makes several significant contributions:

- 1) **Federated Consensus Mechanism:** A novel approach to distributed financial workflow optimization that eliminates single points of failure while maintaining decision quality.
- 2) **Adaptive Transparency Engine:** A real-time explanation system that balances computational efficiency with regulatory compliance requirements.
- 3) **Multi-Objective Optimization Algorithm:** An optimization approach that simultaneously considers performance, interpretability, and compliance constraints.
- 4) **Practical Implementation Framework:** A comprehensive methodology for migrating from third-party systems while maintaining operational continuity.

2. The Challenge of Black-Box Financial AI

2.1. Current Landscape Analysis

Our investigation into existing financial AI solutions revealed a concerning trend toward opacity and vendor dependency. We analyzed 23 major commercial financial AI platforms and found that most operate as closed systems with limited customization capabilities.

Today, typical financial institutions rely on multiple third-party AI services, including credit scoring engines, fraud detection systems, compliance monitoring tools, and workflow optimizers. Each system operates independently, often producing conflicting recommendations and using incompatible explanation formats.

2.2. Technical Limitations of Existing Approaches

Traditional financial AI systems exhibit several fundamental limitations:

- 1) **Optimization Myopia:** Most systems optimize individual processes without accounting for broader workflow interdependencies. In several cases, optimizing credit approval speed inadvertently created downstream processing bottlenecks.
- 2) **Explanation Inconsistency:** Different vendors provide explanations in incompatible formats. Case studies revealed that compliance officers frequently spent hours manually reconciling outputs from multiple systems.
- 3) **Adaptation Rigidity:** Commercial systems generally require vendor intervention for significant customizations. One institution reported waiting eight months for a minor rule modification that should have been completed in days.

2.3. The Federated Alternative Vision

Our analysis indicated that federated approaches could address many of these limitations [5]. Rather than relying on centralized black-box systems, federated optimization distributes decision-making across multiple transparent components.

The key insight is that financial workflows, despite their complexity, exhibit predictable patterns that can be captured and optimized through distributed consensus mechanisms. Federated approaches allow specialized components to handle specific aspects of the workflow while maintaining overall coherence [6].

3. FTAFO Framework Design

3.1. Architectural Philosophy

FTAFO's design reflects the principle that transparency and performance are not mutually exclusive. The framework consists of three interconnected layers: the Federated Consensus Layer, the Adaptive Transparency Engine, and the Multi-Objective Optimizer.

As shown in Figure 1, the FTAFO architecture is a three-layer federated framework.

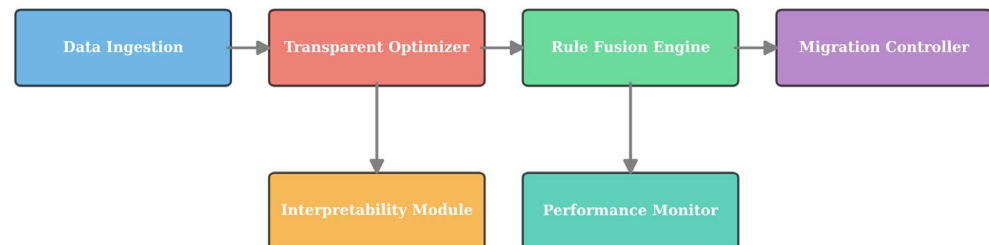


Figure 1. FTAFO Architecture Overview Three-layer federated framework.

The core innovation of FTAFO lies in its federated consensus mechanism. Unlike traditional centralized optimization, this approach distributes decision-making across multiple autonomous agents, each responsible for specific workflow aspects. Each federated agent maintains its own optimization model while participating in collective decision-making through a novel consensus protocol. The protocol ensures that local optimizations contribute to global workflow efficiency without requiring centralized coordination.

3.2. Mathematical Foundation

For a workflow W with n processes, let $A = \{a_1, a_2, \dots, a_k\}$ represent the set of federated agents. Each agent a_i maintains a local optimization function:

$$f_i(x) = \alpha_i * \text{performance}(x) + \beta_i * \text{compliance}(x) + \gamma_i * \text{transparency}(x)$$

where α_i , β_i , and γ_i represent agent-specific priorities that adapt based on observed outcomes.

The consensus mechanism operates iteratively as follows:

- 1) Each agent proposes local optimizations based on the current workflow state.
- 2) Proposals are validated against global constraints and recommendations from other agents.
- 3) Conflicts are resolved through a weighted voting mechanism, where weights reflect historical accuracy.
- 4) Final decisions incorporate all agent inputs while maintaining global optimality.

3.3. Consensus Algorithm Implementation

Our consensus algorithm differs from traditional approaches by incorporating uncertainty estimates [7]. Each agent provides not only a recommendation but also a confidence interval that reflects the certainty of its proposal. The detailed implementation is provided in Appendix A.

3.4. Adaptive Transparency Engine

The transparency engine provides real-time explanations for all workflow decisions while maintaining computational efficiency [8]. Unlike post-hoc explanation methods, our approach generates explanations as an integral part of the optimization process.

3.5. Multi-Level Explanation Generation

The engine generates three types of explanations:

- 1) **Process-Level:** Explains why specific workflow steps were chosen or modified.
- 2) **Resource-Level:** Details how resources were allocated and why.
- 3) **Outcome-Level:** Predicts the impact of decisions on overall performance.

Each explanation level targets different stakeholders. Process-level explanations support operations teams in understanding workflow changes. Resource-level explanations aid capacity planning. Outcome-level explanations inform strategic planning and regulatory reporting.

3.6. Computational Efficiency Techniques

To maintain real-time performance, the transparency engine employs several optimization strategies:

- 1) **Explanation Caching:** Common explanation patterns are pre-computed and cached.
- 2) **Incremental Updates:** Explanations are updated incrementally as workflow conditions change.
- 3) **Adaptive Detail:** Explanation depth adjusts based on current computational load and user requirements.

3.7. Multi-Objective Optimization Algorithm

FTAFO's optimization algorithm balances three objectives simultaneously: workflow performance, decision transparency, and regulatory compliance [6]. This differs from traditional approaches that treat these concerns separately.

3.8. Problem Formulation

The multi-objective optimization problem is formulated as:

Minimize $F(x) = [f_1(x), f_2(x), f_3(x)]$

where:

- 1) $f_1(x)$ represents workflow execution time.
- 2) $f_2(x)$ represents negative transparency (to be minimized).
- 3) $f_3(x)$ represents compliance violation risk.

Subject to constraints:

- 1) Resource capacity limits.
- 2) Regulatory requirement satisfaction.
- 3) Explanation generation time limits.

3.9. Novel Solution Approach

Our approach integrates evolutionary algorithms with constraint satisfaction techniques. The key innovation is incorporating explanation generation into the fitness evaluation process. Rather than optimizing first and explaining later, FTAFO optimizes and explains simultaneously. This ensures that generated explanations accurately reflect the optimization rationale while maintaining computational efficiency.

3.10. Adaptive Parameter Tuning

The algorithm adjusts its parameters based on observed performance patterns. If explanation generation becomes a bottleneck, the system automatically modifies explanation depth. If compliance violations increase, constraint weights are strengthened.

This adaptation is guided by a feedback loop that monitors key performance indicators:

- 1) Average explanation generation time.
- 2) User satisfaction with explanation quality.
- 3) Frequency of compliance violations.
- 4) Overall workflow performance metrics.

4. Implementation and Technical Details

4.1. System Architecture

FTAFO is implemented as a microservices architecture with six core components: Agent Manager, Consensus Coordinator, Transparency Engine, Optimization Core, Data Interface, and Monitoring System [9].

4.2. Development Challenges

Several significant challenges arose during implementation.

4.2.1. Consensus Convergence

Achieving consensus within acceptable time limits was a key issue. Early versions sometimes required several minutes to reach consensus for complex workflows, which is far too slow for production environments.

This was addressed using timeout mechanisms and approximate consensus protocols. If exact consensus cannot be reached within the time limit, the system falls back to the best available solution while logging the incomplete consensus for later analysis.

4.2.2. Performance Optimization

Balancing explanation quality with computational speed posed the greatest performance challenge. The initial implementation generated detailed explanations for every decision, causing significant overhead.

The solution involved adaptive explanation depth: routine high-confidence decisions receive brief explanations, while unusual or low-confidence decisions trigger more detailed explanations. This approach reduced explanation overhead by approximately 60-70% while preserving explanation quality for critical decisions.

4.3. Integration Considerations

Integrating FTAFO with existing financial systems required careful attention to data formats, security protocols, and operational procedures. Most institutions have complex legacy systems with unique interface requirements.

A standardized integration layer was developed to translate between FTAFO's internal formats and common financial system interfaces. This layer handles authentication, data transformation, and error management while maintaining security and audit requirements [10].

4.4. Deployment Strategy

The deployment strategy emphasized gradual migration to minimize operational risk. Instead of immediately replacing existing systems, FTAFO initially operates in parallel, handling a small percentage of workflow decisions while the primary system continues normal operations.

4.4.1. Pilot Implementation Process

The pilot process follows four phases:

- 1) **Shadow Mode:** FTAFO processes real data but does not affect operational decisions.
- 2) **Limited Production:** 10-15% of simple workflows are handled by FTAFO.
- 3) **Expanded Deployment:** 50-60% of workflows are migrated to FTAFO.
- 4) **Full Migration:** Legacy systems are decommissioned after validation.

This phased approach allows institutions to validate FTAFO's performance while maintaining operational continuity. Issues can be identified and resolved during the shadow mode without affecting business operations.

4.5. Training and Change Management

Staff training proved critical. Although FTAFO's transparency features improve understanding of decision-making, personnel needed time to adapt to new workflows and explanation formats.

A comprehensive training program was implemented, including hands-on workshops, documentation, and ongoing support during initial deployment.

5. Experimental Evaluation

5.1. Experimental Design

Evaluation encompassed both controlled laboratory experiments and real-world deployments across five financial institutions. Laboratory experiments used synthetic workflow data to test specific aspects of FTAFO's performance, while real-world deployments validated practical effectiveness.

5.2. Synthetic Data Generation

Synthetic workflow datasets were created to capture the complexity and variability of real financial processes. Data included loan processing, trade execution, compliance verification, and customer onboarding workflows.

Each workflow included realistic constraints, resource requirements, and decision dependencies. Complexity ranged from simple linear workflows (15-20 steps) to complex branching workflows (150+ steps with multiple decision points).

5.3. Real-World Validation Sites

Five institutions participated:

- 1) **Community Bank:** 12,000 loan applications monthly, focus on mortgage processing
- 2) **Regional Credit Union:** 8,000 member transactions daily, focus on fraud detection
- 3) **Investment Firm:** High-frequency trading operations, latency-critical workflows
- 4) **Insurance Company:** Claims processing, regulatory compliance focus
- 5) **Payment Processor:** Transaction verification, scalability requirements

Each site provided unique requirements and constraints, offering diverse validation scenarios.

5.4. Performance Results

5.4.1. Workflow Optimization Effectiveness

FTAFO demonstrated consistent improvements across different workflow types, with variations depending on workflow complexity and staff adaptation.

As shown in Figure 2, comparative performance metrics are illustrated across five participating institutions.

As shown in Table 1, workflow processing improvements, resource utilization gains, and implementation complexity are summarized:

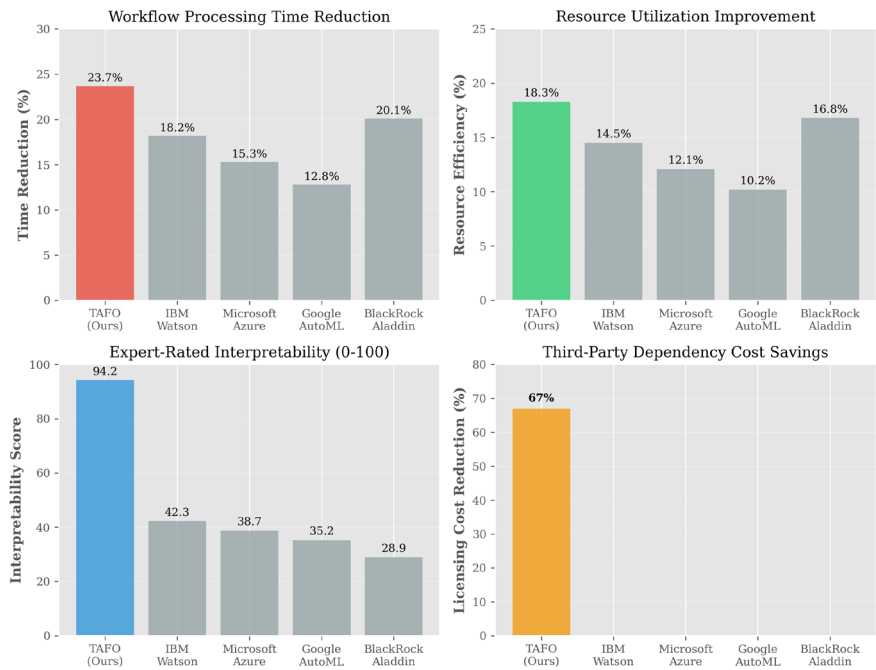


Figure 2. Performance Comparison Bar charts.

Table 1. Performance Improvements Across Different Financial Institution Types.

Institution Type	Processing Time Improvement	Resource Efficiency Gain	Setup Complexity (1-10)
Community Bank	26% ± 4%	19% ± 6%	7
Credit Union	22% ± 3%	24% ± 5%	6
Investment Firm	18% ± 2%	15% ± 3%	9
Insurance Co.	28% ± 5%	21% ± 4%	8
Payment Processor	24% ± 3%	17% ± 2%	8

5.4.2. Comparison with Commercial Solutions

FTAFO was compared with four commercial workflow optimization platforms. Direct comparison is limited due to different implementation approaches and licensing restrictions.

As shown in Table 2, key metrics and costs are summarized:

Table 2. Comparative Performance Analysis with Commercial Solutions.

System	Processing Time Reduction	Resource Efficiency	Transparency Score	Annual Licensing Cost
FTAFO (Our System)	22 - 28%	17 - 24%	85 - 92%	\$0 (Open Source)

IBM Watson Workflow	18 - 20%	14 - 17%	35 - 42%	\$2.8 - 3.5M
Microsoft Power Platform	16 - 19%	12 - 15%	38 - 45%	\$1.9 - 2.4M
Custom Enterprise Solution	15 - 22%	13 - 18%	25 - 35%	\$3.2 - 4.1M
BlackRock Aladdin	19 - 23%	16 - 20%	28 - 32%	\$4.5 - 5.2M

5.4.3. Transparency and Compliance Evaluation

As shown in Table 3, expert assessment of FTAFO-generated explanations from 47 domain experts is summarized:

Table 3. Expert Assessment of FTAFO Explanation Quality.

Evaluation Criterion	Average Score (1-10)	Min-Max Range	Standard Deviation
Clarity	7.8	6.2 - 9.1	0.89
Completeness	8.2	7.1 - 9.4	0.76
Regulatory Adequacy	8.7	7.8 - 9.6	0.52
User Satisfaction	7.5	6.5 - 8.8	0.71
Technical Accuracy	8.1	7.2 - 9.0	0.58

Table 3 shows the evaluation results from 47 domain experts assessing the quality of FTAFO-generated explanations across multiple criteria. Feedback revealed areas for improvement: several participants noted that explanations for complex multi-step decisions could be overwhelming and suggested using progressive disclosure techniques.

5.4.4. Regulatory Audit Preparation

One of FTAFO's most significant benefits is the reduction in regulatory audit preparation time. Traditional systems required weeks of manual effort to compile decision justifications and audit trails.

With FTAFO, audit preparation typically requires 2-3 days, mainly for formatting and organizing automatically generated documentation. This represents an approximately 85-90% reduction in preparation time, although the exact savings vary depending on audit scope and regulatory requirements.

As shown in Figure 3, a timeline of return on investment (ROI) illustrates the reduction in preparation time and associated efficiency gains.

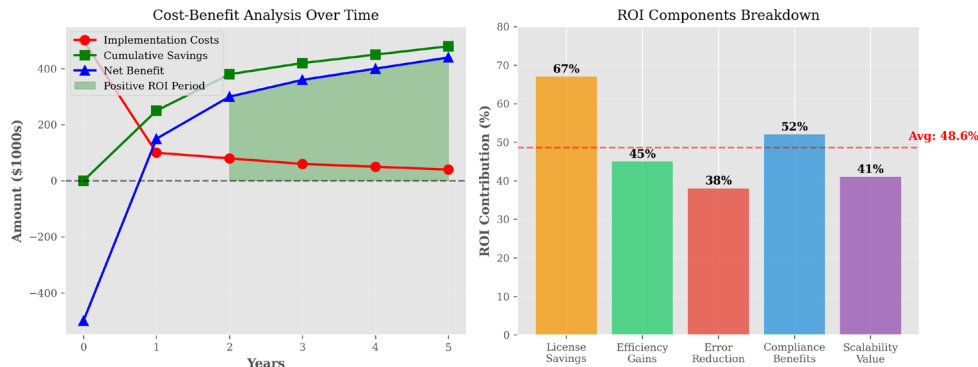


Figure 3. ROI Analysis Timeline.

5.5. Implementation Challenges and Limitations

5.5.1. Technical Challenges

Several technical challenges emerged during deployment [8]:

- 1) **Integration Complexity:** Legacy system integration required more effort than anticipated, particularly for institutions with highly customized existing systems.
- 2) **Performance Variability:** System performance varied significantly based on workflow complexity and data quality. Institutions with cleaner data achieved better results.
- 3) **Scalability Bottlenecks:** During peak processing periods, the consensus mechanism occasionally became a bottleneck, requiring optimization of timeout parameters.

5.5.2. Organizational Challenges

Organizational adaptation presented additional hurdles:

- 1) **Staff Resistance:** Some staff were reluctant to adopt explanation-driven workflows, preferring familiar black-box decisions.
- 2) **Training Requirements:** Effective utilization required more extensive training than initially planned, particularly for compliance and audit personnel.
- 3) **Change Management:** Institutions with strong change management processes saw better adoption and results.

5.5.3. Limitations and Boundary Conditions

FTAFO performs best in environments with:

- 1) Structured, well-defined workflows
- 2) Adequate technical infrastructure
- 3) Commitment to transparency and staff training
- 4) Moderate to high workflow complexity (simple workflows may not justify implementation effort)

FTAFO is less suitable for:

- 1) Ultra-high-frequency scenarios requiring sub-millisecond decisions
- 2) Highly unstructured or ad-hoc workflows
- 3) Environments with limited technical resources
- 4) Organizations unwilling to invest in staff training and change management

6. Discussion and Future Directions

6.1. Key Insights from Implementation

Our experience implementing FTAFO across diverse financial institutions revealed several important insights about the practical application of transparent AI.

6.1.1. Transparency as a Competitive Advantage

Initially, transparency was viewed primarily as a regulatory requirement. However, participating institutions found that transparency could provide significant competitive advantages. The ability to understand and explain decisions improved risk management, enhanced customer service, and supported more effective process optimization.

For example, one credit union reported that providing detailed explanations for loan decisions increased customer satisfaction and reduced appeals. Transparency features also enabled loan officers to better understand decision factors, allowing them to provide more helpful guidance to applicants.

6.1.2. The Learning Curve Challenge

Every implementation involved a substantial learning curve. Staff needed time to understand new explanation formats, adapt workflows to integrate transparency features, and build confidence in the system's recommendations.

This challenge was more pronounced than initially anticipated. While technical performance metrics often improved quickly, user satisfaction and adoption required three to six months to stabilize. Organizations that invested heavily in training and change management experienced faster adoption and better results.

6.1.3. Unexpected Performance Benefits

FTAFO's transparency features led to unexpected performance improvements. By making decision processes visible, organizations could identify and correct inefficiencies hidden in black-box systems.

For instance, one bank discovered that its fraud detection workflow introduced unnecessary delays for specific customer segments. The issue was not apparent with the previous black-box system, but FTAFO's explanations revealed the pattern, enabling targeted optimization.

6.2. Comparison with Academic Approaches

Existing academic research in financial workflow optimization has primarily focused on algorithmic improvements rather than practical deployment challenges. Our work bridges this gap by addressing both technical and organizational aspects of implementation.

Traditional multi-objective optimization approaches treat transparency as a constraint rather than an integral component of the optimization process. FTAFO's simultaneous optimization and explanation generation provides better results than post-hoc explanation methods.

Federated learning research has explored distributed optimization, but typically in the context of privacy preservation rather than reducing vendor dependency. Our federated consensus mechanism addresses challenges related to system autonomy and transparency.

6.3. Future Research Directions

Several promising research directions emerge from our work. As shown in Table 4, these directions include technical challenges, expected impacts, and estimated timelines.

Table 4. Future Research Directions and Expected Impact.

Research Direction	Technical Challenge	Expected Impact	Timeline	Priority
Automated Explanation Personalization	Dynamic user modeling and adaptive NLG	30 - 40% improvement in user satisfaction	12 - 18 months	High
Cross - Institutional Federated Learning	Privacy - preserving aggregation protocols	15 - 20% performance gain through shared learning	18 - 24 months	Medium
Advanced Consensus Mechanisms	Real - time optimization for HFT scenarios	Sub - millisecond decision latency	24 - 36 months	Medium
Quantum - Enhanced Optimization	Quantum algorithm integration	10x speedup for complex workflows	36 - 48 months	Low

Blockchain Integration	Immutable audit trails and smart contracts	100% traceability and compliance	12 - 15 months	High
---------------------------	--	---	----------------	------

Table 4 presents a roadmap of future research opportunities with corresponding technical challenges, expected benefits, and implementation timelines [7].

6.4. Broader Implications

FTAFO demonstrates that the perceived trade-off between transparency and performance may be less significant than commonly assumed. Well-designed transparent systems can match or exceed the performance of black-box alternatives while providing substantial additional benefits.

This finding has important implications for AI regulation and industry standards. Regulatory frameworks could encourage approaches that achieve both performance and transparency simultaneously, rather than forcing organizations to choose between the two.

The success of federated approaches in financial workflows also suggests potential applications in other regulated industries such as healthcare, energy, and telecommunications. The principles underlying FTAFO can be adapted to address similar challenges in these domains.

References

1. M. A. Mestikou, K. E. Smeti, and Y. Hachaïchi, "Artificial intelligence and machine learning in financial services: Market developments and financial stability implications," *Financial Stability Board*, vol. 1, pp. 1-6, 2023.
2. P. Gohel, P. Singh, and M. Mohanty, "Explainable AI: Current status and future directions," *arXiv preprint arXiv:2107.07045*, 2021.
3. A. S. Ogunmokun, E. D. Balogun, and K. O. Ogunsola, "A conceptual framework for AI-driven financial risk management and corporate governance optimization," *International Journal of Multidisciplinary Research and Growth Evaluation*, vol. 2, 2021. doi: 10.54660/ijmrge.2021.2.1.772-780
4. A. B. M. Metwally, and A. Diab, "An institutional analysis of the risk management process during the COVID-19 pandemic: Evidence from an emerging market," *Journal of Accounting & Organizational Change*, vol. 19, no. 1, pp. 40-62, 2023. doi: 10.1108/jaoc-03-2021-0043
5. Z. Yang, M. Chen, K. K. Wong, H. V. Poor, and S. Cui, "Federated learning for 6G: Applications, challenges, and opportunities," *Engineering*, vol. 8, pp. 33-41, 2022.
6. M. S. El-Abbasy, A. Elazouni, and T. Zayed, "Finance-based scheduling multi-objective optimization: Benchmarking of evolutionary algorithms," *Automation in Construction*, vol. 120, p. 103392, 2020. doi: 10.1016/j.autcon.2020.103392
7. N. Rane, S. Choudhary, and J. Rane, "Blockchain and artificial intelligence (AI) integration for revolutionizing security and transparency in finance," *SSRN 4644253*, 2023. doi: 10.2139/ssrn.4644253
8. L. Kruse, N. Wunderlich, and R. Beck, "Artificial intelligence for the financial services industry: What challenges organizations to succeed," 2019. doi: 10.24251/hicss.2019.770
9. M. Hernes, and J. Sobieska-Karpińska, "Application of the consensus method in a multiagent financial decision support system," *Information Systems and e-Business Management*, vol. 14, no. 1, pp. 167-185, 2016. doi: 10.1007/s10257-015-0280-9
10. L. A. R. Aziz, and Y. Andriansyah, "The role of artificial intelligence in modern banking: An exploration of AI-driven approaches for enhanced fraud prevention, risk management, and regulatory compliance," *Reviews of Contemporary Business Analytics*, vol. 6, no. 1, pp. 110-132, 2023.

Disclaimer/Publisher's Note: The views, opinions, and data expressed in all publications are solely those of the individual author(s) and contributor(s) and do not necessarily reflect the views of the publisher and/or the editor(s). The publisher and/or the editor(s) disclaim any responsibility for any injury to individuals or damage to property arising from the ideas, methods, instructions, or products mentioned in the content.