Parallel Financial Systems: Towards Governable and Sustainable Intelligent Financial Services

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ABSTRACT Contemporary financial systems operate in complex environments marked by volatility, uncertainty, complexity, and ambiguity, which elevates the cost of trial and error and exposes the limits of siloed data and centralized control. Considering the complexity challenges for the legacy financial system, we propose the parallel financial systems, which are grounded in the theory of parallel intelligence and utilize the ACP (Artificial systems, Computational experiments, and Parallel execution) methodology to conduct financial execution and resource coordination through the interaction and co-evolution of real-world and artificial systems. Based on this paradigm, we construct a corresponding technical architecture that integrates cutting-edge intelligent technologies represented by AI agents with decentralized technologies provided by blockchain, smart contracts and decentralized autonomous organizations (DAOs). To further demonstrate the applicability for the legacy enterprise, we detail the system workflow, from individual operation to group coordination, with an illustrative example of how the parallel financial systems are utilized along a project lifecycle. This work serves as a theoretical basis and design roadmap for verifiable, privacy-preserving, and interoperable financial intelligence.

INDEX TERMS Financial System, Parallel Intelligence, AI Agent, Web 3.0, DAO

I. INTRODUCTION

In contemporary enterprises, the financial systems are not only the passive repository for transactions and bookkeeping, but also function as a strategic nexus that links corporate objectives to operational execution. Internally, the financial systems constitute core decision-support infrastructures for improving organizational efficiency by transforming dispersed data and processes into actionable managerial information [1]. In tandem with tax administration and internal control compliance, it constrains business activities within institutional and regulatory boundaries, thereby mitigating operational and compliance risks, while playing a pivotal role in managing cash liquidity, working capital, and power structure. Externally, the financial systems operate as credibility-bearing infrastructure that communicates the firms' condition to markets and regulators [2]. Through compliant financial reporting and regulatory filings, it systematically presents the firm's financial position, performance, and cash flows. In interactions with investors, creditors, rating agencies, and tax authorities, it provides verifiable and auditable information that reduces information asymmetry and the cost of capital, thereby strengthening the firm's standing in capital markets and along the value chain.

Financial decision-making entails a very high cost of trial and error, and any improvement in efficiency requires the reliable, trustworthy, and efficient coordination of data and algorithms [3], [4]. However, in real-world settings that involve collaboration among multiple agents and integration across heterogeneous systems with multiple tasks and constraints, existing information systems for finance face layered complexities that arise from dynamic, high-frequency, and multimodal data streams. Externally, the business environment is evolving at high speed and exhibits the well-known volatility, uncertainty, complexity, and ambiguity (VUCA) characteristics [5]. Moreover, negative samples and small-sample long-tail financial data for training decision models are inherently scarce and difficult to label [6]. Internally, current financial systems commonly rely on centralized infrastructures for data custody and identity authorization, which concentrate critical processes and access points in a few nodes and a single identity provider, which is prone to single points of failure, privacy leakage, and cascading breakdowns [7]. In addition, organizational units often suffer from data silos [8], which force firms and auditors to devote considerable resources to source tracing, metric harmonization, and the reconstruction of the causal chain from business events to accounting vouchers.

Furthermore, the usefulness of a single and static algorithm or model is strongly tied to a specific data domain and task definition, which limits broad transfer and rules out true plug and play [9], [10]. Applying these technologies in isolation or in a piecemeal fashion to financial management and operations lacks an architecture and strategy that can integrate their strengths, which in turn risks duplicated investment, wasted resources, and conflicts between technical choices and business objectives [11]. Consequently, financial intelligence requires a new, systematized paradigm that can validate strategies under low-risk conditions and remain robust under high uncertainty.

Recent advances in AI agents provide a new technical pathway for lowering human–machine interaction barriers and task-orchestration costs in financial intelligence. In the era of foundation models, large language models (LLMs) and multimodal LLMs furnish agents with a unified multimodal cognitive core, which confers capabilities for reasoning, memory, tool use, and self-reflection across multiple databases, tasks, and domains [12]. This enables the dynamic execution of complex workflows in a manner where model capability is primary and tool scheduling provides operational support [13]. As research on finance-related problems has deepened, and as domain-specific foundation models such as BloombergGPT [14] and FinGPT [15] have improved the alignment with financial knowledge, AI agents can employ natural language as the interaction interface within financial processes, which substantially lowers the usage threshold for both financial and non-financial employees.

Building on intelligent human–AI collaboration, the verifiable multi-party data framework of Web 3.0 can serve as the decentralized technological substrate that safeguards secure, transparent, and efficient operation of financial systems. In this framework, blockchain maintains a distributed ledger through collective participation, and triple-entry accounting functions as interorganizational infrastructure for process integration, which binds business and accounting confirmations to the same tamper-resistant record and reduces breakpoints and alignment costs along the business–finance–audit chain [16]. The programmability and automatic execution of smart contracts create auditable trails that are traceable and verifiable, which reduces uncertainty in performance verification and audit costs while improving settlement efficiency [17]. Furthermore, through decentralized autonomous organizations (DAOs) and true autonomous organizations (TAOs) [18], financial systems can be managed by its participants as the primary organizational infrastructure [19], which encodes cross-party rules and incentives into governance procedures, thereby rendering budgeting and authorization more procedural and transparent. This enhances collaborative scalability and organizational resilience under multi-organization

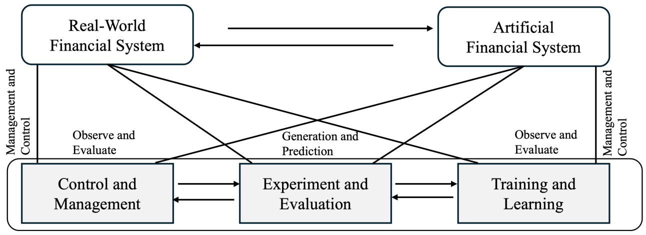

FIGURE 1: Framework of parallel financial systems.

and multi-criteria conditions, while mitigating information asymmetry and ex post opportunism that generate agency risks [20], [21].

The theory of parallel intelligence based on the ACP (artificial societies, computational experiments, and parallel execution) methodology, takes virtual–real interaction and bidirectional close-loop feedback as its core idea [22]. Parallel intelligence effectively integrates emerging intelligent methods with computational experiments so that costly real-world trial and error can be shifted to low-cost virtual experimentation, and which yields a complexity-aware paradigm for guidance and control [23]–[25]. Leveraging parallel intelligence with intelligence technologies represented by AI agents with decentralized technologies represented by blockchain, smart contracts and DAOs, supports the construction of financial systems and operating workflows that are trustworthy, reliable, usable, and cost-effective, which potentially promotes their sustainable development.

In view of the advancement of parallel intelligence theory, enabled by emerging intelligent technologies, this paper develops the parallel financial systems that realize the cyber–physical interactive paradigm and its supporting technical framework. The proposed approach harnesses both intelligent and trust technologies, which aim to provide verifiable, transferable, and auditable interdisciplinary methodologies and technical routes for the management, control, and optimization of complex financial systems. The remainder of the paper proceeds as follows: Section II introduces the concept and theoretical underpinnings of the parallel financial systems; Section III presents the technical architecture and implementation considerations; Section IV describes how the parallel financial systems work; Section V concludes and outlines future directions.

II. PARALLEL FINANCIAL SYSTEM

This section formally introduces the concept of the parallel financial systems and clarifies how, under the paradigm of parallel intelligence, computational experiments can substitute for costly real-world trial-and-error. To further illustrate the connotations of the parallel financial systems, we extracted three key characteristics of the parallel financial systems.

A. BASIC FRAMEWORK

The parallel financial systems are established on the theory of parallel intelligence and the ACP methodology. It constructs one or more artificial financial systems and uses computational experiments to test and evaluate methods for audit, treasury operations, budget coordination, and resource management. Evidence generated at low cost and controlled risk guides execution in the real system. Through parallel execution and bidirectional feedback between the cyber-physical-social systems, a closed loop is formed in which human and machine co-evolve, enabling descriptive diagnostics, predictive inference, and prescriptive steering of the real financial system. As illustrated conceptually in FIGURE 1, the framework comprises three interlocking components of ACP.

1) Artificial Financial System

Using software-defined modeling, digital twins, and generative AI, the real finance function is mapped into a computable virtual environment that integrates internal stakeholders, business assets and venues, and external entities. By combining internal accounting or managerial data, operational and treasury flows, and behavioral traces of past financial decisions with external signals, market volatility, investor sentiment, and firm-related social media dynamics, the system attains descriptive intelligence over the real counterpart. Macro contexts and strategic interactions are further simulated via metaverse constructs, DAOs, and multi-agent systems, yielding one or more artificial financial systems tailored to distinct decision scenarios.

2) Computational Experiments

For scenarios such as project governance, budgeting, asset management, and strategic planning, the artificial system provides a high-fidelity experimental environment. It blends bottom-up approaches with top-down methods to conduct large-scale, parallel evaluation and optimization of processes and policies, thereby supporting risk forecasting, mechanism screening, and parameter calibration. To overcome the paucity of small or negative samples in financial analytics, black-swan and long-tail scenarios are synthesized to enable extensive counterfactual analysis, allowing exploration of alternatives at negligible operational risk and cost, and yielding more robust decision support.

3) Parallel Execution

The real system periodically feeds financial statements, market states, and execution traces into the artificial system, driving continual recalibration of models and reporting bases and shrinking virtual–real gaps. In return, the artificial system emits operationalized recommendations, risk alerts, and runbooks that are enacted—under checkpoints—in the real environment. This two-way closed loop delivers verifiable, controllable, and agile management and optimization of the enterprise finance function.

Within ACP, observation, evaluation, learning, and management proceed in an integrated manner. Finance staff practice budgeting and reconciliation in a sandbox to quantify long-term consequences of alternative choices. While non-finance staff, without touching production systems, could assess how business actions map into financial metrics and resource usage, thereby coordinating budgets, resources, and division of labor more effectively.

B. KEY CHARACTERISTICS

1) Virtual–Real Loop Driven by Data and Knowledge

Parallel financial systems enforce correctness and verifiability through a coupled loop of data, knowledge, and policy. It aggregates accounting and managerial data, business transactions, treasury and cash data, external environmental signals, and audit and compliance evidence. Under conditions where "small" real financial data are scarce, heterogeneous, and misaligned, the system constructs large "WHAT-IF" datasets for experimentation and inference through data generation and recomposition. Generative modeling, adversarial generation, temporal and graph learning, knowledge graphs, and rule engines transform cross-system data into scenario-specific "IF-THEN" micro-knowledge. Each item of micro-knowledge is stored in a knowledge base in a computable form such as rules, strategies, parameter sets, or causal graphs, with provenance, versioning, and scope of validity. For tasks such as budget allocation, treasury scheduling, reconciliation and cross-statement ties, tax planning, and cost attribution, micro-knowledge is assembled into executable micro-intelligence, stress-tested through large-scale A/B and scenario tests in the artificial system, and then deployed in parallel to the real environment. Executed outcomes flow back to update data, knowledge, and policies, producing a continuously evolving virtual–real loop.

2) Distributed human–AI decision making

Parallel financial systems improve responsiveness and organizational resilience through distributed human–AI collaboration. Large foundation models and multimodal agents provide the cognitive core, while finance, business, audit, and tax stakeholders act as coordinated nodes in a decision network. Humans specify objectives, balance values, and handle exceptions; AI agents perform information integration, real-time forecasting, and policy generation. At critical checkpoints, the process employs human-in-the-loop (HITL) governance to balance efficiency, robustness, and compliance. Natural language requests are translated by AI agents into plans that include validation and rollback paths. The agents orchestrate enterprise resource planning (ERP) connectors, invoice and document checks, tax and treasury services, reconciliation and risk tools, and then auto-generate journal entries and payment instructions. Online monitoring detects concept drift, anomalous patterns, and rule obsolescence, which triggers retraining and rule updates, thereby sustaining inclusive, distributed, and accountable decision making.

3) Inclusive and sustainable governance

The parallel financial systems release the collaborative potential of interdepartmental and interorganizational under the organizational and coordinative properties of DAOs. From the organizational perspective, DAOs provide formal representation and verifiable decision rights. Roles and scopes of authority are defined ex ante that align incentives, protect minority interests. Budget authority is delegated through parameterized governance modules that bind approvals to objective criteria and accountable stewards, and all changes to standards and policies are recorded with provenance so that institutional memory is preserved. From the coordination perspective, DAOs couple budget authorization contracts with selective disclosure so that approvals are auditable without revealing plaintext. Execution is synchronized through contract-specified checkpoints and objective triggers that tie business events to financial recognition, while versioned lineage maintains traceability for data transformation and reporting. Inclusive and sustainable governance is realized as a contract-enforced and evidence-driven regime that broadens participation, strengthens accountability, and preserves long-run adaptability.

III. TECHNICAL ARCHITECTURE

This section introduces a comprehensive technical architecture from data infrastructure, execution, to cooperation. Specifically, we first propose a blockchain-based data infrastructure to improve the quality and reliability of financial data, thereby addressing the long-standing disjunction between business operations and financial accounting. On this foundation, agentic execution is incorporated to deliver efficient and intelligent financial shared services for employees across corporate departments, fostering seamless collaboration between finance and other units. To efficiently allocate the existing financial resources, we utilized DAOs to enable an agentic, fair and democratic method of negotiation and cooperation.

A. BLOCKCHAINS-BASED INFRASTRUCTURE

Aiming to provide an accountable and trustworthy data source for the parallel financial systems, this infrastructure is composed of two interlinked consortium chains: the internal management chain (IMC) and the external collaboration chain (ECC). IMC is designed with efficiency as the primary objective. It functions as a highly normalized, event-driven distributed database that prioritizes rapid response and high-frequency updates to reflect the dynamic operations of the enterprise. While ECC prioritizes legal enforceability and auditability. It is structured as a digitalized, programmable registry of contracts and assets, with a data format that is self-contained, transparent, and easy to verify by external stakeholders.

1) Internal management chain

Data categories such as organizational roles, budget allocations, inter-departmental settlements, performance metrics, and policy enforcement are maintained as smart contracts. Participants include employees across various departments, project managers, finance staff, and executive decision-makers. These actors interact with the chain through decentralized identities (DIDs) and digital wallets, with permissions determined by their roles. The chain supports micro-transactions and state changes at high frequency, ensuring that every internal decision is captured and verified in real time, from budget reallocations to reimbursement approvals. Consensus is maintained through a delegated proof-of-stake (DPoS) protocol, where trusted internal nodes validate transactions. Each node is further supported by AI agents that perform autonomous verification tasks, enforce policy compliance, and optimize resource allocation strategies. The result is a self-regulating internal environment that maximizes operational efficiency while preserving data integrity.

2) External collaboration chain

Participants include suppliers, customers, regulatory bodies, banks, and audit firms, each identified by unique DIDs. Smart contracts on this chain govern purchase orders, accounts receivable/payable, financing agreements, and tokenized asset transfers. Compliance checks, tax calculations, and audit verifications are embedded as executable logic, ensuring that every transaction conforms to applicable legal and regulatory frameworks. Consensus is also maintained through DPoS, where AI agents play a critical role by monitoring compliance in real time, conducting automated reconciliations, and issuing alerts when anomalies or risks are detected. This ensures that the external chain not only maintains legal robustness but also builds trust among all collaborating parties.

Blockchain-based data infrastructure bridges the long-standing divide between operations and accounting and enabling common-source integration with reconciled records. DPoS delivers high throughput and low latency for internal operations. Validator nodes embed AI agents that perform rule checks, review blocks, and flag anomalies, reducing human error and improving fraud resistance. Smart contracts ensure atomic transactions, so internal state changes in budgeting, cost accumulation, or performance settlement finalize only when external events such as delivery confirmation or financing approval are satisfied; conversely, external events are routed back to update budgets and financial statements with traceable timestamps. This infrastructure serves as a single truth source that reflects business processes in real time and generates financial records automatically, meeting internal efficiency needs and external requirements for transparency, traceability, and consistency.

B. AGENTS-ENABLED EXECUTION

In traditional finance shared services (FSS) settings, non-finance units have limited access to actionable financial deci-

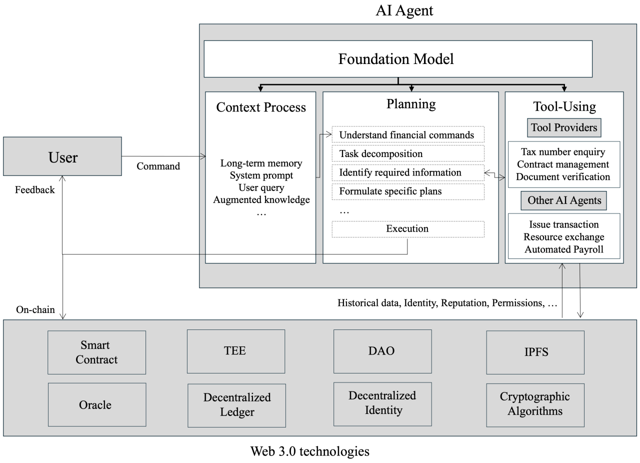

FIGURE 2: Architectural overview of the financial service AI agent.

sion support. As a result, they resort to shadow systems and parallel spreadsheets, which propagate data duplication, definitional drift, and competing governance routines, thereby entrenching departmental boundaries and eroding enterprise-level coordination. To alleviate these structural frictions, this paper introduces an intelligent financial service agents (IFS Agents) designed for organization-wide use as shown in FIGURE 2. The agent combines natural-language interaction with verifiable execution so that all departments can collaborate on a common set of facts and rules, and so that manually designed static prescriptions can be re-expressed as adaptive, context-aware policies.

The IFS Agents comprises three core modules: context process, planning, and tool-using, which ensure semantic consistency, procedural controllability, and auditability.

Context process: This module constructs task context and harmonizes terminology. It maps natural language requests to the firm's canonical semantics and fuses long-term memory, system prompts, user inputs, and retrieved policy, reporting, and history artifacts into an executable context. Configurable prompts and templates impose "soft constraints" that guide downstream reasoning, improve answer consistency and traceability, and facilitate reconstruction of decision rationales for audit.

Planning: Building on the standardized context, this module interprets financial instructions, decomposes tasks, and orchestrates steps. It identifies required information and risk points; encapsulates budgeting, payments, reconciliation, archival review, tax inquiries, and contract checks into reusable plan templates; and embeds checkpoints such as limit controls, authorization checks, cross-statement consistency tests, and key performance indicators (KPI) thresholds. It produces forms, scripts, or workflow specifications, supports parameterization and rollback strategies, and enables consistent execution across business lines and regions.

Tool-using: This module coordinates external capabilities and enforces controlled execution. Via standardized interfaces, it connects to ERP or FSS platforms, tax and registry services, contract and invoice verification, records management and reporting engines, as well as reconciliation and risk tools; it can also collaborate with other AI agents (e.g., procurement, legal, budgeting). Under scoped permissions it performs data retrieval, validation, journal generation, payment and settlement, and evidence archiving. Standard interfaces abstract system heterogeneity and allow hot-plugging of new tools, preserving extensibility and evolvability.

Web 3.0 technologies are tightly coupled to the planning and tool-using stages to deliver trustworthy collaboration and compliance guarantees. Smart contracts encode budgeting rules, authorization matrices, and conditional payments as executable workflows, turning the question of "whether obligations were met" into the certainty of "whether execution can proceed." Oracles securely lift off-chain KPIs, acceptance results, and compliance lists on-chain to serve as triggers, and expose external uncertainty in programmable form for simulation and stress testing. trusted execution environments (TEEs) provide hardware-isolated, privacy-preserving computation for sensitive data and model inference, lowering the risk of cross-unit or cross-firm collaboration. A decentralized ledger records authorizations, disbursements, intercompany settlements, reconciliations, and acknowledgments as an immutable time series, establishing a single source of truth. DIDs issue verifiable identities and credentials to people, departments, and agents, enabling fine-grained permissions and revocable delegation. DAOs embed HITL governance at critical checkpoints via proposal–voting–execution–review, reducing hierarchical friction and improving responsiveness. Interplanetary file system (IPFS) provides content-addressed, versioned storage for proposals, contracts, models or data cards, and audit workpapers, anchored to on-chain hashes for replay and comparison. Cryptographic primitives, including zero-knowledge proofs, enable selective disclosure and proof-of-compliance, reducing third-party review intensity and audit sampling.

As a unified "financial capability entry point," the IFS Agents use natural language to cover the full path from context construction and process planning to controlled execution and on-chain evidencing. Non-finance users can submit colloquial requests to complete budget reallocation, expense reimbursement, contract checks, tax-ID queries, and internal settlements; finance teams gain automated, auditable, and constrained execution with embedded risk control. The result is higher accessibility and interoperability under strict privacy and compliance, fewer shadow processes and data silos, deeper business–finance integration, and an adaptive policy stack that evolves with external uncertainty.

C. DAOS-DRIVEN COOPERATION

Budgeting is a core cooperation mechanism of enterprise resources. Its design and use systematically shape managerial behavior and organizational performance [26]. To further establish a dynamic, auditable, and procedurally fair coordination mechanism for resources through the budgeting manner, we propose the agentic budgeting coordination DAO (ABCDAO) to transform hierarchical budgeting into a decentralized, transparent, and computation-governed collaborative regime.

The primary participants and administrators of ABCDAO are AI agents embedded in individual business units, which deeply integrate HITL mechanism by human employees and financial experts to perform directing, monitoring, and emergency intervention. Each agent is endowed with a DID and acts as an autonomous representative of its unit's interests and analytical capabilities. The core on-chain components include a governance contract, a proposal-and-voting contract, and a budget-authorization contract deployed on the IMC. The governance contract specifies proposal lifecycles, validity criteria, and consensus conditions. The proposal-and-voting contract enables the submission of structured budget proposals and conducts voting according to predefined rules. The budget-authorization contract, contingent on successful governance outcomes, automatically issues verifiable, tamper-evident authorization records with cryptographic signatures as non-repudiable evidence of approved allocations and dispatches execution instructions to off-chain financial systems. Governance proceeds via dynamically weighted voting: each agent's influence is determined by interpretable algorithms that aggregate strategic alignment, historical performance, and simulated cross-unit externalities, thereby aligning local decisions with firm-level objectives.

Substantively, ABCDAO reconstitutes business units as profit centers, closing the loop among authority, responsibility, and rewards within the organization and thereby improving adaptability and survival prospects during adverse shocks [27]. In terms of resource allocation, ABCDAO's decentralized, agent-driven coordination enables proactive and timely capital reallocation and strategic adjustment, potentially to foster durable competitive advantages under high uncertainty. Mechanistically, ABCDAO operates as an internal capital market arrangement in which funds, guided by constraints and performance signals, continually flow toward activities with higher marginal returns, mitigating information silos and the inefficiencies of static budgets. Accordingly, budgeting shifts from a zero-sum contest over resources to a collaborative investment ecosystem: departments evolve from resource claimants to co-creators of value, deepening business–finance integration and supporting sustainable, long-term growth.

IV. SYSTEM WORKFLOW

This section describes how the technical architecture operates from the individual level, the IFS Agents, to the group level, the corresponding ABCDAO, with an illustrated example on how an enterprise layers the parallel financial systems atop existing stacks.

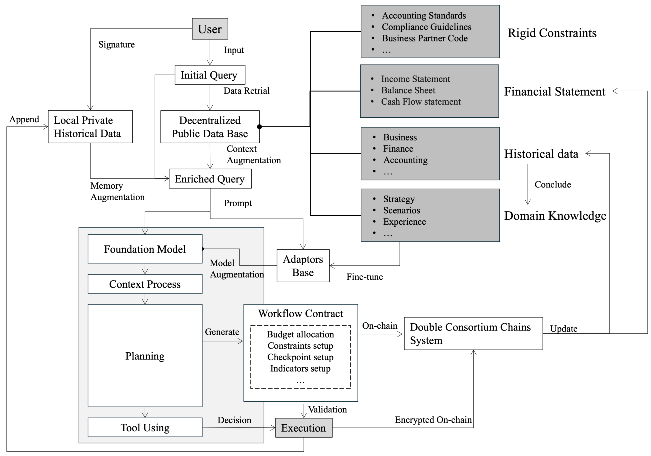

FIGURE 3: The operation mechanism of the IFS.

A. INDIVIDUAL LEVEL OPERATION

The operation of the IFS Agents, as shown in FIGURE 3, integrate data, models, processes, contracts, and evidentiary artifacts into a verifiable end-to-end stack: retrieval- and memory-augmented context building upstream; adaptor-based specialization and constraint-aware decoding midstream to ensure domain consistency and compliance; and workflow contracts plus a dual-consortium-chain design downstream for auditable, traceable process governance. Outcomes are anchored to reporting semantics and key performance indicators to secure business alignment and long-term verifiability.

Progress begins with a signed natural-language or structured request. Within the authorized scope, the system queries both local private history and decentralized public repositories to perform semantic retrieval and data re-extraction, producing a model-ready, context-rich query. Processed by the foundation model and its context pipeline, which is constrained by retrieval augmentation and instruction templates, the query undergoes semantic interpretation, entity and reporting-basis alignment, and task decomposition. Accounting standards and domain knowledge inject hard/soft constraints to keep reasoning strictly within institutional boundaries. For tasks such as budgeting, reconciliation, and report mapping, the system loads lightweight adaptors, which are basically the low-rank adaptor (LoRA) blocks fine-tuned for different scenarios, for fine-grained tuning and behavior correction, and applies constrained decoding with post-hoc calibration to yield a compliance-aware intermediate plan.

The plan is then compiled into an executable workflow contract that specifies budgeting rules, constraint boundaries, checkpoints, and metrics. After sandbox verification off-chain, only key metadata and fingerprints are committed on-chain to establish a non-repudiable, traceable evidence trail. During execution, the agent orchestrates incumbent enterprise tools (e.g., ERP connectors, reconciliation utilities, KPI calculators) and triggers, at designated points, checks for rule consistency, cross-statement ties, and identity or permission validation. Exceptions invoke checkpoint-based rollback and human–machine confirmation to maintain controlled convergence.

Results of the execution will be written back, in standard semantics, to historical and reporting layers, while decentralized public stores and domain knowledge are updated, anchored in reports and metrics. In this way, the system unifies data accessibility, compliance, and auditability in high-velocity business contexts and, with modest interaction and orchestration overhead, continuously delivers reusable, verifiable decision support to both finance and non-finance stakeholders.

B. GROUP LEVEL COORDINATION

ABCDAO is responsible for organizing and coordinating the IFS Agents from different departments. ABCDAO begins with opportunity identification. When agents detect external market shifts or internal efficiency gains that warrant rapid reallocation of working capital, unit-level agents autonomously generate and assess budget proposals using real-time operational data, expected returns, and organizational priorities. Proposals are then broadcast within ABCDAO for collective deliberation and coordination. Peer agents evaluate the net synergistic effects from the vantage point of their own capacity, cash-flow position, and risk tolerance. For example, an agent representing a unit with surplus funds may treat the proposal as an internal investment opportunity and engage in algorithmic bargaining over rate, tenor, and risk-sharing terms; where appropriate, it may interface with decentralized finance protocols (e.g., flash loans) or internal "equity pools" to augment liquidity supply. Such peer-to-peer negotiation replaces cumbersome approval chains with computable market-style games, accelerating convergence to a firm-level optimal allocation of funds. To prevent overly aggressive proposals from undermining system resilience, human stewards in the finance function perform HITL reviews at key checkpoints and may revise or veto proposals based on strategic constraints, ethical boundaries, and contextual judgments. Once consensus is achieved, execution is automated via smart contracts, and both the process and outcomes are streamed back to enterprise information systems for real-time monitoring and compliance auditing. ABCDAO records the complete governance trail, including agent reasoning, voting weights, human interventions, and execution evidence—on-chain in a tamper-evident manner, yielding end-to-end audit trails. These historical records serve as training and evaluation corpora that facilitate subsequent cycles of alignment with documented human preferences, value orientations, and institutional constraints, thereby being potentially able to continually enhance the robustness and trustworthiness of the agents.

C. ILLUSTRATIVE EXAMPLE

During system initialization, the enterprise maps internal employees, external authorities, and affiliated partners to corresponding IFS Agents, and issues DIDs and verifiable credentials to human users and agents under the principle of least privilege, which defines identity and authorizes scoped access. Department-level IFS Agents are assembled via atomic smart contracts to constitute an ABCDAO in which agents act as the primary decision makers and human governors conduct review and exception adjudication, which enables autonomous resource coordination and rule evolution. Physical assets such as equipment and sites are digitized through digital-twin methods, which create computable representations that are connected through API to critical financial functions. The artificial financial system is then constructed by integrating internal accounting and business data, behavioral histories of prior financial decisions and managerial practices, and external data reflecting market fluctuations, investor sentiment, and firm-related social media dynamics, while embedding multitask and multimodal algorithms that provide a structured and transparent computational backbone.

Before a project commences, the parallel financial systems generate a cluster of scenarios within the artificial financial system under the constraints of the firm's medium- and long-term strategy and the operational realities reported by the blockchain-based data substrate, which ensures structural homology with the target context. These scenarios are subsequently reduced and filtered using real-time operating indicators, external macro signals, and near-term project goals. Within the ABCDAO, departmental IFS Agents engage in high-frequency interactions concerning budget allocation, resource occupancy, and risk thresholds, which translate into visual and computational simulations that identify latent bottlenecks, constraint conflicts, and compliance boundaries, thereby yielding executable contingency plans with clearly specified triggers.

During project execution, the parallel financial systems track the trajectory of the real financial system and account for factors that influence budget performance as well as unanticipated events, which motivates the recombination of prior scenarios and the use of computational experiments to enumerate and forecast feasible financial decisions and their workflows. TEEs are instantiated, and IFS Agents invoke adaptors that encode prior task experience to conduct comparative testing and efficacy assessment; when performance under a given scenario is inadequate, the agent constructs and trains a new adaptor online to revise the policy, which preserves specificity and reliability across heterogeneous conditions. Human personnel monitor execution continuously, while financial experts take control at authorization thresholds, in exceptional situations, and at ethical boundaries, which ensures an interpretable balance among efficiency, robustness, and regulatory compliance.

After project completion, the system re-estimates parameters and recalibrates structures in the artificial financial system based on realized financial outcomes and operational performance, which updates cost functions, risk parameters, and compliance thresholds. The calibrated knowledge and policies are then propagated back into budgeting and execution pipelines to support adaptive optimization in the next cycle. In parallel, a virtual learning and training center for financial decision-making is established on top of the artificial financial system, which delivers scenario-based training and controlled evaluations aligned with corporate objectives and unit-level needs. This virtual–physical interaction and closed-loop feedback accelerate experience accumulation and capability transfer, thereby improving the reliability of financial decisions and the robustness of execution outcomes.

V. CONCLUSION

This study introduces the parallel financial systems in which the ACP method provides a low-risk laboratory for policy exploration and a closed loop for virtual–real alignment. On this foundation, we specify a technical architecture that fuses blockchain-enabled data integrity with the AI agent empowered intelligent execution and the DAOs-based resource coordination method. The case study clarifies how the parallel financial systems could be initiated and utilized by the enterprise. Parallel financial systems offer a conceptual foundation and practical blueprint for building trustworthy, interpretable, and robust financial systems.

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