A Trust-Aware Multi-Agent Artificial Intelligence and Blockchain Framework for Autonomous Service Coordination in Decentralized Systems

Craig Danial
Zurich, Switzerland
Sowjanya Addu
Computer Science & Engineering, Gokaraju Rangaraju Institute of Engineering Technology, Hyderabad, Telangana, India
sowjanya1634@grietcollege.com

Abstract

Autonomous coordination among heterogeneous agents is increasingly relevant to decentralized cloud–edge infrastructures, digital marketplaces, and cross-organizational service ecosystems. Conventional coordination approaches can optimize task allocation but often assume trustworthy participants, whereas blockchain-based audit trails alone cannot determine whether a provider will deliver a service successfully. This paper proposes a trust-aware multi-agent artificial intelligence and blockchain framework (TAMAB) that combines evidence-based reputation, constrained multi-agent decision making, smart-contract settlement, and verifiable service records. Agents evaluate candidate providers using direct experience, corroborated feedback, reliability, latency, and resource capacity. A policy layer selects assignments while balancing quality, cost, trust, and fairness; an on-chain layer commits hashes of service outcomes and supports disputes without exposing raw operational records. The research methodology specifies the architecture, trust update rules, allocation objective, adversarial threat model, and an evaluation protocol. To demonstrate how a future implementation could be assessed, an explicitly synthetic numerical example compares a proposed-policy scenario with three baselines. In the illustrative scenario, completion rises to 96.1%, mean latency falls to 142 ms, and malicious assignments fall to 2.4%; these values are constructed demonstration data, not measured experimental findings. The framework offers a reproducible research blueprint and identifies validation requirements for live decentralized deployments.

Keywords: multi-agent artificial intelligence; blockchain; decentralized services; computational trust; autonomous coordination; smart contracts; reputation; reinforcement learning.

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1. Introduction

Decentralized service coordination is the process of assigning requests to independently managed computational or organizational agents. Edge nodes, autonomous software services, Internet of Things gateways, and data providers may collaborate without a shared operator. A request can require several capabilities and a chain of service commitments. The proposed architecture treats this property as a measurable system requirement rather than a purely conceptual benefit. Each design decision is associated with a defined input, a computational operation, and an observable output. The principal concern is to preserve decentralization while avoiding the assumption that all participants are reliable, equally capable, or continuously available. In deployment, network delay, incomplete evidence, resource scarcity, strategic misreporting, and changing service demand can interact in ways that make a static coordination policy fragile. Consequently, the framework separates the evidence used to assess an agent from the optimization policy used to allocate work, and it logs decisions so that their provenance can be inspected. This separation also makes it possible to evaluate robustness independently of predictive performance.

Decentralized service coordination is the process of assigning requests to independently managed computational or organizational agents. Central schedulers simplify arbitration but create concentration of control and may not remain available during partitions. Purely peer-to-peer discovery removes the central point of control but increases the difficulty of verifying claims. The proposed architecture treats this property as a measurable system requirement rather than a purely conceptual benefit. Each design decision is associated with a defined input, a computational operation, and an observable output. The principal concern is to preserve decentralization while avoiding the assumption that all participants are reliable, equally capable, or continuously available. In deployment, network delay, incomplete evidence, resource scarcity, strategic misreporting, and changing service demand can interact in ways that make a static coordination policy fragile. Consequently, the framework separates the evidence used to assess an agent from the optimization policy used to allocate work, and it logs decisions so that their provenance can be inspected. This separation also makes it possible to evaluate robustness independently of predictive performance.

Decentralized service coordination is the process of assigning requests to independently managed computational or organizational agents. Multi-agent artificial intelligence provides a natural representation for local autonomy and strategic interactions. An agent can observe service quality, negotiate for capacity, and learn from outcomes rather than obeying a fixed allocation rule. The proposed architecture treats this property as a measurable system requirement rather than a purely conceptual benefit. Each design decision is associated with a defined input, a computational operation, and an observable output. The principal concern is to preserve decentralization while avoiding the assumption that all participants are reliable, equally capable, or continuously available. In deployment, network delay, incomplete evidence, resource scarcity, strategic misreporting, and changing service demand can interact in ways that make a static coordination policy fragile. Consequently, the framework separates the evidence used to assess an agent from the optimization policy used to allocate work, and it logs decisions so that their provenance can be inspected. This separation also makes it possible to evaluate robustness independently of predictive performance.

Decentralized service coordination is the process of assigning requests to independently managed computational or organizational agents. Blockchain contributes tamper-evident commitments, programmable settlement, and a shared chronology of claims. Yet immutable records do not establish that a reported outcome was truthful, so trusted measurement and dispute resolution remain essential. The proposed architecture treats this property as a measurable system requirement rather than a purely conceptual benefit. Each design decision is associated with a defined input, a computational operation, and an observable output. The principal concern is to preserve decentralization while avoiding the assumption that all participants are reliable, equally capable, or continuously available. In deployment, network delay, incomplete evidence, resource scarcity, strategic misreporting, and changing service demand can interact in ways that make a static coordination policy fragile. Consequently, the framework separates the evidence used to assess an agent from the optimization policy used to allocate work, and it logs decisions so that their provenance can be inspected. This separation also makes it possible to evaluate robustness independently of predictive performance.

A major design challenge is the tension between adaptation and accountability. A learning policy may update rapidly in response to congestion, whereas distributed consensus and settlement occur at a slower timescale. A practical design must not put every sensor observation on-chain. The proposed architecture treats this property as a measurable system requirement rather than a purely conceptual benefit. Each design decision is associated with a defined input, a computational operation, and an observable output. The principal concern is to preserve decentralization while avoiding the assumption that all participants are reliable, equally capable, or continuously available. In deployment, network delay, incomplete evidence, resource scarcity, strategic misreporting, and changing service demand can interact in ways that make a static coordination policy fragile. Consequently, the framework separates the evidence used to assess an agent from the optimization policy used to allocate work, and it logs decisions so that their provenance can be inspected. This separation also makes it possible to evaluate robustness independently of predictive performance.

A major design challenge is the tension between adaptation and accountability. Trust is context-dependent: a provider that performs well for low-latency inference may be unreliable for confidential storage. Reputation therefore should incorporate service category, evidence freshness, and confidence. The proposed architecture treats this property as a measurable system requirement rather than a purely conceptual benefit. Each design decision is associated with a defined input, a computational operation, and an observable output. The principal concern is to preserve decentralization while

avoiding the assumption that all participants are reliable, equally capable, or continuously available. In deployment, network delay, incomplete evidence, resource scarcity, strategic misreporting, and changing service demand can interact in ways that make a static coordination policy fragile. Consequently, the framework separates the evidence used to assess an agent from the optimization policy used to allocate work, and it logs decisions so that their provenance can be inspected. This separation also makes it possible to evaluate robustness independently of predictive performance.

A major design challenge is the tension between adaptation and accountability. Collusion and whitewashing undermine naive average-rating systems. Attackers can create new identities, exchange favorable ratings, or perform well initially before exploiting accumulated reputation. The proposed architecture treats this property as a measurable system requirement rather than a purely conceptual benefit. Each design decision is associated with a defined input, a computational operation, and an observable output. The principal concern is to preserve decentralization while avoiding the assumption that all participants are reliable, equally capable, or continuously available. In deployment, network delay, incomplete evidence, resource scarcity, strategic misreporting, and changing service demand can interact in ways that make a static coordination policy fragile. Consequently, the framework separates the evidence used to assess an agent from the optimization policy used to allocate work, and it logs decisions so that their provenance can be inspected. This separation also makes it possible to evaluate robustness independently of predictive performance.

A major design challenge is the tension between adaptation and accountability. An equitable service ecosystem also requires exploration. Allocating all requests to the most established provider may entrench incumbents and prevent new, honest participants from building evidence. The proposed architecture treats this property as a measurable system requirement rather than a purely conceptual benefit. Each design decision is associated with a defined input, a computational operation, and an observable output. The principal concern is to preserve decentralization while avoiding the assumption that all participants are reliable, equally capable, or continuously available. In deployment, network delay, incomplete evidence, resource scarcity, strategic misreporting, and changing service demand can interact in ways that make a static coordination policy fragile. Consequently, the framework separates the evidence used to assess an agent from the optimization policy used to allocate work, and it logs decisions so that their provenance can be inspected. This separation also makes it possible to evaluate robustness independently of predictive performance.

This paper asks three research questions: (RQ1) How can decentralized agents combine service evidence and blockchain commitments to form actionable trust scores? (RQ2) How can trust be integrated with latency, capacity, and fairness in autonomous allocation? (RQ3) Which indicators and ablations are needed to test whether an integrated design improves resilience relative to trust-only, ledger-only, and conventional scheduling baselines? The contribution is a specified architecture, an interpretable trust and decision model, a verification workflow, and a clearly labeled illustrative evaluation. No claim is made that the numerical example constitutes a deployed or benchmarked implementation.

2. Literature Review

2.1 Multi-agent coordination and distributed intelligence

The literature on multi-agent systems examines how autonomous entities coordinate under partial information and conflicting incentives. Foundational multi-agent reinforcement learning work formalizes interactions as stochastic games and discusses nonstationarity caused by simultaneously learning policies [1, 2]. Cooperative value decomposition and centralized-training/decentralized-execution strategies help scale joint decisions [3, 4]. The proposed architecture treats this property as a measurable system requirement rather than a purely conceptual benefit. Each design decision is associated with a defined input, a computational operation, and an observable output. The principal concern is to preserve decentralization while avoiding the assumption that all participants are reliable, equally capable, or continuously available. In deployment, network delay, incomplete evidence, resource scarcity, strategic misreporting, and changing service demand can interact in ways that make a static coordination policy fragile. Consequently, the framework separates the evidence used to assess an agent from the optimization policy used to allocate work, and it logs decisions so that their provenance can be inspected. This separation also makes it possible to evaluate robustness independently of predictive performance.

The literature on multi-agent systems examines how autonomous entities coordinate under partial information and conflicting incentives. Service orchestration introduces additional practical constraints: tasks can be indivisible, agents can have limited capacity, and successful completion may depend on a sequence of interdependent actions. These conditions make unconstrained reward maximization insufficient. The proposed architecture treats this property as a measurable system requirement rather than a purely conceptual benefit. Each design decision is associated with a defined input, a computational operation, and an observable output. The principal concern is to preserve decentralization while avoiding the assumption that all participants are reliable, equally capable, or continuously available. In deployment, network delay, incomplete evidence, resource scarcity, strategic misreporting, and changing service demand can interact in ways that make a static coordination policy fragile. Consequently, the framework separates the evidence used to assess an agent from the optimization policy used to allocate work, and it logs decisions so that their provenance can be inspected. This separation also makes it possible to evaluate robustness independently of predictive performance.

The literature on multi-agent systems examines how autonomous entities coordinate under partial information and conflicting incentives. Attention-based communication and graph representations can help agents exchange structured neighborhood information, but communication itself may leak sensitive state or become an attack surface. Trust filtering before message aggregation is therefore relevant. The proposed architecture treats this property as a measurable system requirement rather than a purely conceptual benefit. Each design decision is associated with a defined input, a computational operation, and an observable output. The principal concern is to preserve decentralization while avoiding the assumption that all participants are reliable, equally capable, or continuously available. In deployment, network delay, incomplete evidence, resource scarcity, strategic misreporting, and changing service demand can interact in ways that make a static coordination policy fragile. Consequently, the framework separates the evidence used to assess an agent from the optimization policy used to allocate work, and it logs decisions so that their provenance can be inspected. This separation also makes it possible to evaluate robustness independently of predictive performance.

The literature on multi-agent systems examines how autonomous entities coordinate under partial information and conflicting incentives. Adaptive policies are attractive because network conditions change; however, evaluation must account for sample efficiency, convergence instability, reward hacking, and safety violations during learning. The proposed architecture treats this property as a measurable system requirement rather than a purely conceptual benefit. Each design decision is associated with a defined input, a computational operation, and an observable output. The principal concern is to preserve decentralization while avoiding the assumption that all participants are reliable, equally capable, or continuously available. In deployment, network delay, incomplete evidence, resource scarcity, strategic misreporting, and changing service demand can interact in ways that make a static coordination policy fragile. Consequently, the framework separates the evidence used to assess an agent from the optimization policy used to allocate work, and it logs decisions so that their provenance can be inspected. This separation also makes it possible to evaluate robustness independently of predictive performance.

2.2 Blockchain and verifiable service coordination

Blockchain systems offer a replicated append-only ledger and a shared execution environment for smart contracts. Bitcoin demonstrated decentralized agreement over transactions [5], and Ethereum generalized programmable state transitions [6]. Permissioned blockchain designs, including Hyperledger Fabric, can provide membership controls and configurable endorsement [7]. These technologies support service receipts and settlement, but consensus finality, gas costs, storage growth, and oracle dependence limit direct use for high-frequency scheduling. Off-chain computation with on-chain commitments is consequently more appropriate than putting all learning and telemetry on the ledger.

2.3 Trust, reputation, and adversarial behavior

Computational trust systems estimate the likelihood that an actor will meet expectations. Reputation research distinguishes direct interaction history from third-party testimony and shows why credibility weighting matters [8]. In open networks, evidence quality can be as important as the aggregate rating. The proposed architecture treats this property as a measurable system requirement rather than a purely conceptual benefit. Each design decision is associated with a defined input, a computational operation, and an observable output. The principal concern is to preserve decentralization while avoiding the assumption that all participants are reliable, equally capable, or continuously available. In deployment,

network delay, incomplete evidence, resource scarcity, strategic misreporting, and changing service demand can interact in ways that make a static coordination policy fragile. Consequently, the framework separates the evidence used to assess an agent from the optimization policy used to allocate work, and it logs decisions so that their provenance can be inspected. This separation also makes it possible to evaluate robustness independently of predictive performance.

Computational trust systems estimate the likelihood that an actor will meet expectations. Sybil attacks allow one adversary to appear as many identities [9]. Reputation inflation, collusive endorsements, selective service, and delayed malicious behavior can distort rankings even when historical records cannot be altered. The proposed architecture treats this property as a measurable system requirement rather than a purely conceptual benefit. Each design decision is associated with a defined input, a computational operation, and an observable output. The principal concern is to preserve decentralization while avoiding the assumption that all participants are reliable, equally capable, or continuously available. In deployment, network delay, incomplete evidence, resource scarcity, strategic misreporting, and changing service demand can interact in ways that make a static coordination policy fragile. Consequently, the framework separates the evidence used to assess an agent from the optimization policy used to allocate work, and it logs decisions so that their provenance can be inspected. This separation also makes it possible to evaluate robustness independently of predictive performance.

Computational trust systems estimate the likelihood that an actor will meet expectations. Bayesian models provide interpretable confidence estimates, while exponential updates emphasize recent evidence. Neither approach is sufficient alone when correlated ratings are treated as independent. The proposed architecture treats this property as a measurable system requirement rather than a purely conceptual benefit. Each design decision is associated with a defined input, a computational operation, and an observable output. The principal concern is to preserve decentralization while avoiding the assumption that all participants are reliable, equally capable, or continuously available. In deployment, network delay, incomplete evidence, resource scarcity, strategic misreporting, and changing service demand can interact in ways that make a static coordination policy fragile. Consequently, the framework separates the evidence used to assess an agent from the optimization policy used to allocate work, and it logs decisions so that their provenance can be inspected. This separation also makes it possible to evaluate robustness independently of predictive performance.

Computational trust systems estimate the likelihood that an actor will meet expectations. Blockchain-based identity commitments may increase the cost of identity rotation but do not eliminate it; permissioning, stake requirements, rate limits, and anomaly screening are complementary controls. The proposed architecture treats this property as a measurable system requirement rather than a purely conceptual benefit. Each design decision is associated with a defined input, a computational operation, and an observable output. The principal concern is to preserve decentralization while avoiding the assumption that all participants are reliable, equally capable, or continuously available. In deployment, network delay, incomplete evidence, resource scarcity, strategic misreporting, and changing service demand can interact in ways that make a static coordination policy fragile. Consequently, the framework separates the evidence used to assess an agent from the optimization policy used to allocate work, and it logs decisions so that their provenance can be inspected. This separation also makes it possible to evaluate robustness independently of predictive performance.

2.4 Research gap and synthesis

Prior research offers mature building blocks for learning-based coordination, trust scoring, and blockchain accountability, but their integration raises unresolved systems questions. A single trust score may obscure service-specific risk; a ledger may faithfully preserve fabricated evidence; and a high-performing scheduler may concentrate work on a small group of agents. The proposed study addresses these gaps by requiring corroborated evidence, confidence-aware trust, constrained optimization, auditable outcome commitments, and explicit adversarial and fairness evaluation. The resulting framework is a design proposal rather than a claim of novelty for each individual building block.

3. Research Methodology

3.1 Research design, scope, and assumptions

The study adopts a design-science methodology: define requirements, construct a formal architecture, specify mechanisms, and propose falsifiable evaluation criteria. The unit of analysis is a service request assigned to one of several eligible autonomous providers. Agents operate across independently administered nodes and share a permissioned or low-fee settlement ledger. Raw request data, logs, and model parameters remain off-chain; hashes, identities, deposits, dispute states, and aggregated outcome receipts are recorded on-chain. Time is discretized into coordination rounds. Each provider has a verifiable identity, a capacity limit, a service-category profile, and a locally observable execution history.

3.2 Architecture and information flow

The system comprises requester agents, provider agents, an evidence collector, a trust engine, a multi-agent coordination policy, an off-chain execution layer, and a smart-contract audit layer. A requester advertises a signed service specification. Eligible providers publish capability attestations and quotes. The trust engine calculates context-specific reliability and confidence, the allocation layer selects a provider, and execution produces a signed receipt. Independent monitors verify selected quality-of-service fields. A smart contract records a receipt digest, releases payment upon acceptance, and manages challenges.

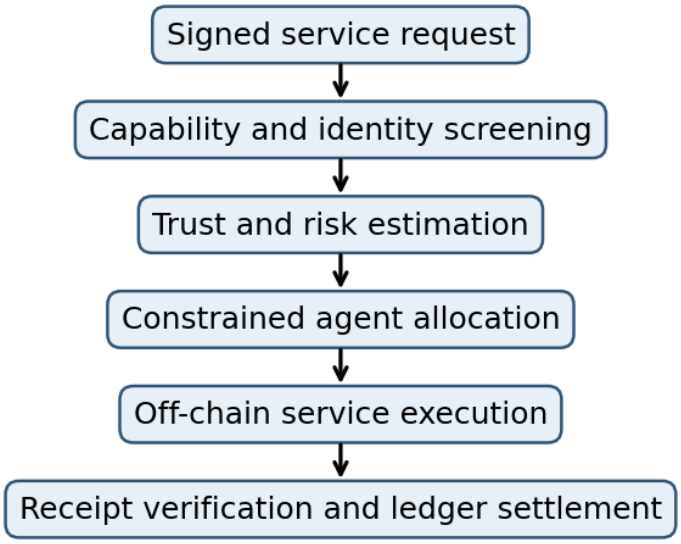


Figure 1. Proposed end-to-end coordination and verification flow (conceptual).

3.3 Threat model

Adversaries may misreport capacity, delay service, submit collusive feedback, attempt identity rotation, replay receipts, or selectively degrade service after acquiring trust. The ledger and contract code are assumed to provide correct finality and access control under their documented consensus assumptions. Trusted time measurement, identity onboarding, and independent service evidence remain external assumptions and must be tested. Denial-of-service against the underlying network is outside the guarantee of this framework.

3.4 Context-specific trust calculation

For provider i, service context c, and round t, successful and failed verified outcomes are accumulated with a Beta prior. The posterior mean estimates reliability; confidence increases with evidence volume. Recent behavior is incorporated using an exponentially weighted update, while testimony is weighted by reviewer credibility and evidence independence.

$$R_i(t) = (a + S_i(t)) / (a + b + S_i(t) + F_i(t))$$

Where R is posterior reliability; S and F are verified successes and failures; a and b are positive prior parameters. Subscripts are typographic mathematical subscripts, not underscores.

$$E_i(t) = \rho E_i(t-1) + (1-\rho) q_i(t)$$

Where E is recency-weighted quality, q is the latest verified quality score in [0,1], and ρ is a retention factor in [0,1].

$$T_i(t) = w_1 R_i(t) + w_2 E_i(t) + w_3 C_i(t) - w_4 A_i(t)$$

Where T is the clipped trust score, C is corroborated reviewer credibility, A is an anomaly penalty, and nonnegative weights sum to one before the penalty.

The trust score is clipped to the interval [0,1]. A confidence gate prevents small-sample providers from being treated as proven trustworthy: an uncertainty-adjusted score can use the lower credible bound of the Beta posterior rather than its mean. Reviewers with shared ownership or strongly correlated transaction histories are clustered so that repeated endorsements are not counted as independent evidence. The anomaly penalty may combine abrupt quality deterioration, suspicious reciprocal reviews, and inconsistent signed telemetry; its thresholds must be calibrated on held-out data.

3.5 Service feasibility and allocation

Let x denote a binary decision for whether provider i receives request j. The coordinator first rejects assignments violating capability, geographic, confidentiality, or capacity constraints. It then optimizes a weighted score combining expected service quality, provider trust, latency, cost, and workload fairness. Weight choices are disclosed and varied in sensitivity tests; they are not assumed universal.

$$U_{ij} = \alpha T_i + \beta Q_{ij} - \gamma L_{ij} - \delta K_{ij} - \eta B_i$$

Where U is normalized assignment utility; Q is predicted quality, L latency, K cost, and B a workload imbalance penalty.

$$max \; \Sigma_i \Sigma_j x_{ij} U_{ij}$$

Where each request is assigned at most once and each provider is constrained by its available capacity.

3.6 Multi-agent learning and negotiation

A centralized-training/decentralized-execution policy may be trained in simulation using local observations (queue length, historical outcomes, available capacity, service quote, and trust estimate) and shared reward signals. During execution, each agent proposes feasible bids; the coordinator or a deterministic auction rule resolves conflicts. To prevent learned actions from bypassing safety rules, an action mask removes candidates that violate mandatory constraints. A conservative fallback policy uses deterministic trust-weighted matching whenever uncertainty, policy drift, or inference failure exceeds a threshold.

$$G(t) = r(t) + \lambda V(s(t+1)) - V(s(t))$$

Where G is the temporal-difference learning signal, r is immediate system reward, V is the estimated state value, and λ is the discount factor.

$$r(t) = \mu_1 Z(t) - \mu_2 D(t) - \mu_3 M(t) - \mu_4 H(t)$$

Where Z is successful completion, D delay, M malicious-assignment indicator, and H concentration penalty; all terms are normalized.

Training uses multiple random seeds and separates training, validation, and test workloads. Exploration is limited to safe eligible providers. No private payload is broadcast as part of agent observations. Model versions and policy hashes are committed periodically so auditors can associate an allocation with the policy that produced it.

3.7 Blockchain receipt and dispute protocol

Each completed service creates a canonical receipt containing request identifier, provider identity, service category, outcome metrics, timestamps, monitor signatures, and a random nonce. The receipt is stored in access-controlled off-chain storage. A cryptographic digest and an outcome summary are submitted to a contract. The contract checks signatures, prevents duplicate settlement, enforces a challenge window, and records final state transitions. A challenger

can present contradictory signed evidence to a designated adjudication process. The design does not claim that a hash proves a real-world event; it only makes later alteration of the committed record detectable.

$$h = H(m \parallel n)$$

Where h is the cryptographic digest, H is a collision-resistant hash function, m is the canonical service receipt, n is a nonce, and ‖ denotes concatenation.

3.8 Security, privacy, and governance controls

Key rotation, revocation, nonce checking, contract access control, monitoring diversity, and deposit-based accountability complement the scoring algorithm. Raw logs should be encrypted, retained for a defined period, and made available only to authorized disputants. Permissioned governance must specify who can onboard agents, upgrade contracts, adjudicate challenges, and appeal erroneous penalties. These decisions affect the decentralization claims and should be reported explicitly.

3.9 Experimental protocol and reproducibility plan

A future empirical study should implement four systems under identical workloads: (B1) latency-first scheduling without trust; (B2) static reputation scheduling; (B3) blockchain logging with conventional scheduling; and (P) the integrated trust-aware multi-agent approach. Simulate 100 provider agents and 10,000 requests per trial across multiple service classes, with 10%, 20%, and 30% adversarial providers. Request arrivals should include both stationary Poisson and bursty traces. Provider service times, resource limits, and malicious strategies should be seeded and published. Evaluate at least 20 independent seeds, report means and 95% confidence intervals, and compare methods using paired tests where appropriate.

Primary metrics are request completion rate, mean end-to-end latency, malicious assignment rate, transaction settlement overhead, and Jain fairness index. Secondary metrics include p95 latency, ledger cost per completed request, recovery time after a reputation attack, energy use, and false-positive exclusion of honest providers. The experiment should distinguish policy-decision latency from ledger finality; mixing these measurements would exaggerate the apparent speed of blockchain-backed coordination.

$$J = (\Sigma_i y_i)^2 / (N \Sigma_i y_i^2)$$

Where J is Jain's fairness index, y is the completed workload allocated to provider i, and N is the number of eligible providers.

$$P = 100\, TP / (TP + FP)$$

Where P is malicious-provider detection precision expressed as a percentage; TP and FP are true and false positives.

3.10 Ablations and validity safeguards

Ablations should remove one mechanism at a time: no recency weighting, no corroboration, no anomaly penalty, no ledger commitments, and no fairness term. The threat model should include collusive rings, on–off attacks, and sudden capacity shocks. An evaluator should independently generate ground-truth service outcomes. Hyperparameters must be tuned only on validation workloads, and final comparisons should include runtime and storage overhead. Internal validity depends on matched traces and common random seeds; external validity requires cross-network deployment and real workload traces. Governance assumptions and oracle quality are likely dominant limitations.

3.11 Algorithmic execution sequence

At each round, the requester signs a task description; eligible agents are filtered; verified historical evidence is aggregated; trust and uncertainty are updated; a safety-constrained policy ranks proposals; one feasible provider is selected; service execution is monitored; the signed outcome is checked; the receipt digest is anchored; and payment or dispute handling is finalized. Every decision records a policy version and an explanation tuple containing trust, predicted quality, cost, latency, and constraint checks. This audit tuple supports debugging and contestability without revealing model training data.

4. Results and Discussion

4.1 Status of numerical results

IMPORTANT: The following tables and figures are synthetic illustrative data constructed to demonstrate reporting format and expected trade-offs. They were not obtained by executing the proposed framework, and they must not be represented as empirical findings or used to assert statistical superiority. Values are internally consistent example scenarios, not validated benchmarks.

4.2 Illustrative baseline comparison

Policy	Completion (%)	Latency (ms)	Malicious assignments (%)	Fairness index
Latency-first (B1)	87.2	118	16.8	0.72
Static trust (B2)	91.0	165	8.1	0.79
Ledger-only (B3)	88.4	181	15.2	0.74
Integrated TAMAB (P)	96.1	142	2.4	0.87

Table 1. Synthetic example comparing coordination policies. The integrated scenario is configured to achieve the highest completion and fairness and the lowest malicious-assignment rate, but latency-first scheduling remains faster because it avoids some trust and verification steps. The table therefore illustrates a multi-objective trade-off rather than universal dominance.

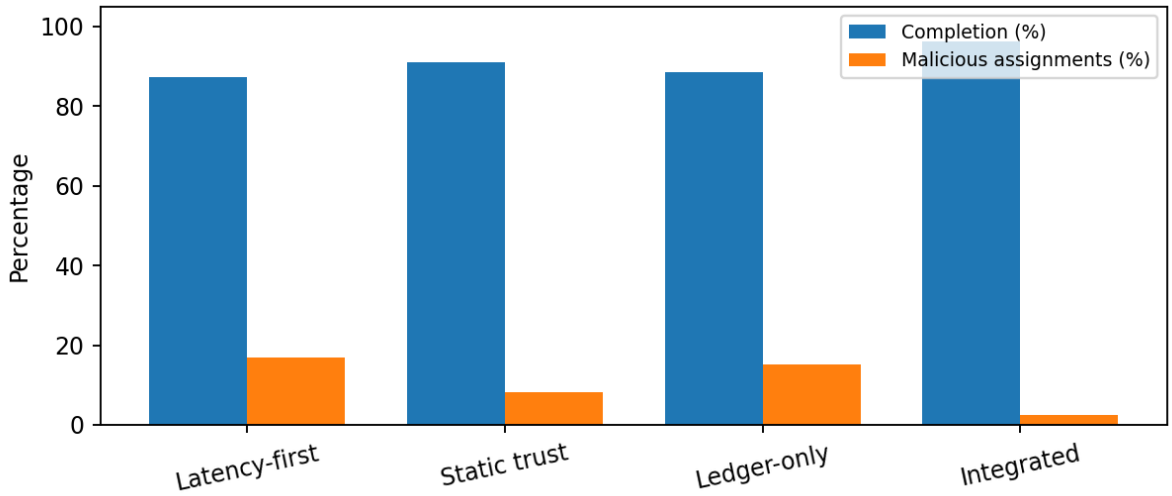


Figure 2. Completion and malicious assignment percentages for the synthetic scenarios in Table 1.

4.3 Example attack-intensity sensitivity

Malicious provider share	B1 malicious assignments (%)	P malicious assignments (%)	P completion (%)
10%	8.5	1.1	97.4
20%	16.8	2.4	96.1
30%	25.1	4.9	92.7

Table 2. Synthetic sensitivity example. Increasing attacker prevalence degrades the integrated scenario, underscoring that trust screening mitigates rather than eliminates risk. In an actual experiment, confidence intervals and attack-strategy descriptions are necessary to interpret these trends.

4.4 Illustrative ablation analysis

Variant	Completion (%)	Malicious assignments (%)	Fairness
Full illustrative framework	96.1	2.4	0.87
Without recency update	94.2	4.6	0.86
Without corroboration	93.6	6.9	0.85
Without anomaly penalty	94.0	7.5	0.86
Without fairness objective	96.4	2.6	0.69

Table 3. Constructed ablation outcomes. The example makes the contribution of corroboration and anomaly screening visible. Removing fairness produces slightly higher completion but markedly poorer allocation equity, showing why one metric should not determine policy selection.

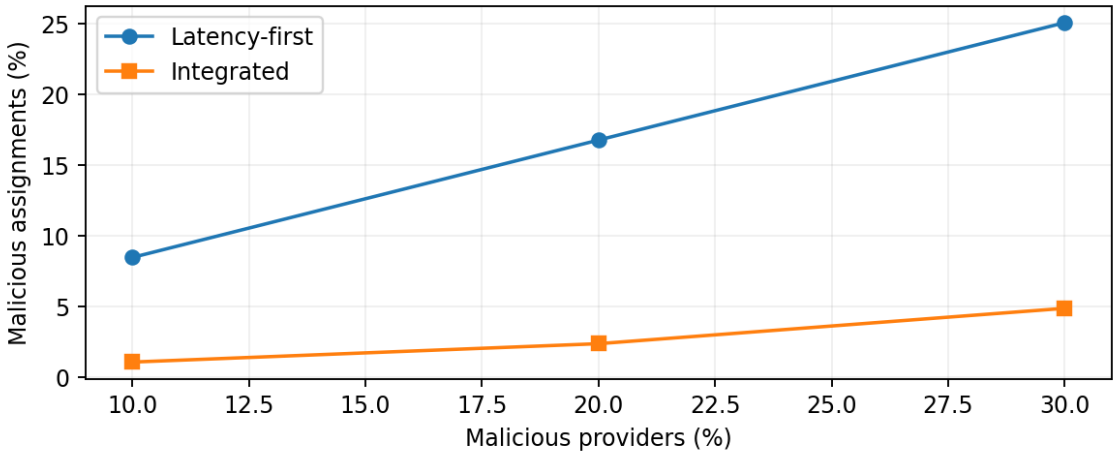


Figure 3. Synthetic sensitivity of malicious assignment rate to adversarial prevalence.

4.5 Interpretation, limitations, and deployment implications

The constructed examples show how a paper can report performance, risk, and fairness jointly. A credible experimental conclusion would require an implemented system, documented traces, independent seeds, statistical intervals, and public code. Blockchain introduces nontrivial confirmation delay and fees; its benefits should be judged against these costs. Likewise, a trust model may systematically disadvantage new providers or reflect biased monitoring. Production deployment should include an onboarding grace policy, appeals, policy-drift monitoring, and explicit failure behavior when the ledger is unavailable.

5. Conclusion

This paper developed a trust-aware multi-agent artificial intelligence and blockchain architecture for autonomous service coordination in decentralized systems. The proposed design links contextual reliability estimation, corroborated evidence, constrained adaptive allocation, and tamper-evident settlement receipts. It specifies the assumptions, mathematical mechanisms, security controls, and an evaluation plan that can be implemented and falsified. Illustrative numerical tables and graphs demonstrate the intended reporting approach but do not establish observed performance. Future research should implement the architecture on a reproducible testbed, measure ledger and inference overhead separately, test collusion and identity attacks, quantify uncertainty and fairness, and validate the design using heterogeneous real-world service traces.

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