

Trust Scoring Model for Real Estate Brokers using Blockchain Based Reputation Graphs

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Abstract

Trust in real estate brokerage remains a critical challenge due to asymmetric information, inconsistent regulations, and the prevalence of unverifiable or subjective reputation signals. Existing trust mechanisms, such as customer reviews, brokerage licensing data, and institutional accreditation, suffer from centralization, susceptibility to manipulation, and a lack of verifiable provenance. Blockchain technology offers a distributed infrastructure for recording immutable, transparent, and tamper-resistant data; however, current blockchain-based trust models largely focus on financial transactions and do not integrate complex, multi-party trust interactions such as those found in real estate ecosystems. This study proposes a blockchain-driven trust scoring model for real estate brokers using a novel Reputation Graph framework. The model integrates agent interactions, verified transactions, peer endorsements, dispute outcomes, and temporal performance signals into a decentralized trust propagation graph executed through smart contracts. Trust is mathematically computed using a hybrid of weighted PageRank, Bayesian updating, and multi-edge semantic scoring to reflect the multidimensional nature of broker credibility. The proposed architecture enables trust computation without central intermediaries while ensuring auditability and resistance to collusion and Sybil attacks. Experimental simulations demonstrate that the model maintains stable trust distributions under adversarial conditions, provides more accurate trust separation between high- and low-performing brokers, and reduces vulnerability to fake interactions. The proposed approach can serve as a foundation for decentralized credibility infrastructures across real estate marketplaces, multi-broker networks, online listing platforms, and property tokenization ecosystems.

Keywords

Blockchain reputation systems; decentralized trust; real estate brokers; trust propagation; reputation graphs; smart contracts; PageRank; Bayesian trust.

1. Introduction

Trust remains one of the most fundamental determinants of successful real estate transactions. Unlike purely digital marketplaces, real estate brokerage involves high-value, infrequent, and legally binding commitments that require buyers and sellers to rely heavily on the credibility of intermediaries. Brokers perform multiple critical functions: property valuation, documentation support, negotiation, regulatory

compliance, and market education, yet the trustworthiness of these actors is often difficult to verify. Conventional mechanisms, such as customer reviews, licensing registries, referral networks, and platform-level rating systems, provide only partial and often unverifiable indicators of broker performance. As a consequence, real estate markets continue to experience information asymmetry, opportunistic behaviour, and broker misconduct, all of which reduce market efficiency and increase transaction risk [1].

Centralized trust infrastructures introduce additional limitations. Platform-controlled rating systems, for example, maintain unilateral authority over reputation data. Such systems lack transparency, are vulnerable to manipulation, and cannot provide cryptographic assurance of data integrity. Furthermore, ratings are typically aggregated using simplistic arithmetic averages that fail to capture the complexity of multi-dimensional trust signals. The absence of a standardized, tamper-resistant, and verifiable global trust layer for broker performance remains a major structural gap in the real estate domain [2, 3].

Blockchain technology offers a promising foundation for addressing these limitations. Distributed ledger systems ensure data immutability, resist unauthorized manipulation, and support decentralized verification. Blockchain-based trust models have been explored in financial services, peer-to-peer marketplaces, and supply chain networks [4]. However, the real estate brokerage ecosystem presents unique challenges: interactions are multi-party, trust signals are heterogeneous, and outcomes often depend on temporal performance patterns rather than discrete events. Existing blockchain applications in real estate primarily focus on property tokenization, land registries, and transaction notarization rather than broker-level credibility assessment [5, 6]. As a result, there is a lack of blockchain-native frameworks specifically designed to model and quantify trust in real estate intermediaries [7].

To address this gap, this study introduces a blockchain-based Trust Scoring Model grounded in Reputation Graphs, leveraging graph theory, smart contracts, and probabilistic trust propagation [8]. Reputation graphs represent brokers as nodes and trust-expressing events such as completed transactions, peer verifications, conflict resolutions, and customer endorsements as weighted, timestamped edges [9]. Unlike traditional rating systems, graph-based frameworks capture relational trust patterns, allowing the model to express both direct and indirect trust flows. By incorporating blockchain, the system ensures each interaction is verifiable, cryptographically linked to its originator, and immutable [10].

Furthermore, this work proposes a hybrid trust calculation mechanism combining weighted PageRank, Bayesian updating, and multi-edge semantic weighting. Weighted PageRank captures global trust flow by considering how credibility propagates through broker networks. Bayesian updating allows incremental adjustments to trust based on new evidence, reducing volatility from isolated events. Multi-edge semantic weighting differentiates trust signals by their type, source, and verifiability, ensuring that regulatory verifications, successful dispute resolutions, and high-value transaction completions contribute more significantly to trust scores than low-impact endorsements [11].

An additional contribution of this research is the formalization of a Decentralized Reputation Architecture, wherein all trust-related interactions are recorded on a blockchain ledger and interpreted by smart contracts [12]. This design eliminates the reliance on centralized third parties, enabling a trust ecosystem governed by transparent, auditable rules. The system also incorporates countermeasures against Sybil attacks, collusion clusters, fabricated endorsements, and temporal gaming of trust scores [13].

The proposed model addresses several research questions that have not been sufficiently examined in the literature

1. How can real estate brokers' trust be modelled as a computable, multi-dimensional reputation structure rather than a simplistic rating metric?
2. What blockchain primitives and smart contract designs are required to verify, store, and govern reputation interactions without centralized intermediaries?
3. Which trust propagation algorithms accurately reflect the dynamic, relationship-driven nature of real estate brokerage credibility?
4. How resilient is a decentralized reputation graph to adversarial behaviours common in digital trust systems, such as collusion and identity forgery?

By addressing these questions, this research contributes a rigorous architectural, mathematical, and algorithmic foundation for decentralized reputation computation in real estate markets [14].

The main contributions of this paper are summarized as follows

1. A blockchain-based reputation graph model tailored for real estate brokerage trust. The study defines a multi-edge graph structure capturing diverse trust events with semantic and temporal attributes.
2. A hybrid trust scoring methodology integrating weighted PageRank, Bayesian probability updating, and semantic edge weighting to derive robust, attack-resistant trust scores.
3. A decentralized architecture using smart contracts to store trust events, validate brokers, govern scoring rules, and ensure system transparency without centralized authorities [15].
4. A formal threat and adversarial analysis, evaluating the model's resistance to collusion, Sybil attacks, malicious event injection, and rating bias [16].
5. An experimental framework and simulation results demonstrating the performance, stability, and discriminatory power of the proposed trust model [17].

The remainder of this paper is organized as follows. Section 2 reviews existing literature on trust systems, blockchain-based reputation models, and graph-theoretic trust propagation mechanisms. Section 3 presents the theoretical foundations of trust modelling and decentralized reputation graphs. Section 4 describes the proposed trust scoring model, including graph construction, smart contract logic, and mathematical formulations. Section 5 outlines the system architecture and algorithms. Section 6 presents the experimental environment, dataset generation, and evaluation metrics. Section 7 reports results and analysis. Section 8 discusses model implications, limitations, and deployment considerations. Finally, Section 9 concludes the study and outlines directions for future work [18].

2. BACKGROUND AND RELATED WORK

Trust modelling has been extensively studied across distributed systems, online marketplaces, peer-to-peer networks, and semantic web environments. Although the real estate domain involves unique multi-party interactions and high-value transactions, foundational concepts from these domains offer relevant theoretical and methodological insights. This section synthesizes literature on classical trust models,

graph-based reputation computation, blockchain-enabled trust infrastructures, and limitations of existing real estate reputation mechanisms. The aim is to contextualize the research gap addressed by the proposed decentralized trust scoring model.

2.1 Classical Trust Models

Early computational trust frameworks focused on quantifying trust between agents in distributed systems. Marsh's seminal trust model formalized trust as a measurable, context-dependent value bound by situational constraints [1]. Subsequent models expanded on this by incorporating direct experiences, risk tolerance, and environmental factors. Despite their conceptual richness, classical models were constrained by centralized data aggregation and lacked mechanisms for verifiable provenance of trust signals.

Other foundational trust models include Abdul-Rahman and Hailes' recommendation-based systems, which emphasized direct and indirect evidence from peers [2]. Jøsang's belief model introduced probabilistic representations of trust, enabling uncertainty handling through opinions composed of belief, disbelief, and uncertainty components [3]. Although powerful in environments with fluctuating confidence and partial information, these models assumed that trustworthy evidence was authentic and tamper-free, an assumption rarely satisfied in adversarial or commercially competitive ecosystems.

In digital marketplaces, eBay-style rating systems emerged as the dominant trust mechanism. These systems rely heavily on user-generated feedback aggregated into simplistic summary metrics. While accessible, rating systems are widely criticized for vulnerability to spam, fabricated reviews, unilateral deletion by platform administrators, and limited semantic granularity. Additionally, the aggregation methods do not reflect trust propagation or differentiate between the significance of high-stakes and low-stakes transactions [4, 5].

Overall, classical trust models establish fundamental constructs for measuring agent credibility but fail to address provenance, multi-dimensionality, and adversarial manipulation limitations that blockchain-based systems aim to overcome [6].

2.2 Graph-Based Reputation Systems

Graph-based reputation models conceptualize trust relationships as directed weighted graphs, enabling computation of global trust through structural analysis. PageRank, originally developed for web ranking, has become a foundational algorithm for evaluating importance and credibility in large networks. In trust systems, PageRank distributes trust scores through the graph based on the connectivity and credibility of neighbouring nodes [7].

HITS (Hyperlink-Induced Topic Search) further distinguish nodes into hubs and authorities, which is useful in environments where agents perform differentiated trust roles [8]. Trust propagation models, such as EigenTrust and PeerTrust, extend these approaches to peer-to-peer networks by incorporating transaction satisfaction levels and normalization across global networks. These algorithms demonstrate strong theoretical underpinnings but assume that rating inputs are accurate and resistant to manipulation conditions rarely satisfied in minimally regulated domains like real estate brokerage [9, 10].

Reputation graphs in the semantic web community aim to represent trust semantically by enriching edges with metadata such as interaction type, timestamp, and reliability. Ontology-based trust models allow for more expressive reasoning but require robust mechanisms for data validation and disambiguation. Moreover, semantic trust graphs still depend on trusted intermediaries for verification, limiting their applicability in competitive or adversarial domains [11].

In summary, graph-based systems provide a scalable mathematical foundation for modelling trust propagation but require a tamper-resistant infrastructure to ensure authenticity and resilience. Blockchain technology offers such an infrastructure by serving as an immutable ledger for trust events [12].

2.3 Blockchain-Enabled Trust Models

Blockchain's potential as a trust layer has been extensively explored in decentralized marketplaces, IoT environments, cross-organization workflows, and identity management. Smart contracts facilitate automated enforcement of rules governing interactions, while cryptographic data structures ensure immutability and auditability. These properties make blockchain a suitable substrate for decentralized reputation systems [13].

Several blockchain-based reputation models have been proposed. Some leverage transaction histories from public ledgers to infer trust, particularly in cryptocurrency trading contexts. Others utilize smart contracts to validate feedback submissions and prevent Sybil attacks by associating transactions with blockchain identities [14]. However, these models typically rely on direct financial transfers or discrete interactions, making them less applicable to domains characterized by heterogeneous trust signals, such as real estate brokerage [15].

More advanced blockchain reputation systems incorporate differential weighting, credibility decay, temporal factors, and penalty scoring for dishonesty or disputes. Nonetheless, most existing models are platform-centric (e.g., decentralized marketplaces) rather than agent-centric (e.g., professional brokers), and they seldom incorporate multi-edge semantic graphs or hybrid probabilistic scoring mechanisms [16].

Additionally, fully decentralized blockchain governance of reputation data remains an open challenge. Many existing models depend on off-chain data sources for verification, introducing trust bottlenecks. For real estate brokers, trustworthiness involves complex blends of transactional performance, peer endorsements, regulatory compliance, and customer satisfaction. Therefore, blockchain alone is insufficient without graph structures and semantic weightings capable of capturing this heterogeneity [17].

2.4 Real Estate Trust Mechanisms

This study makes three key contributions to advancing trust assessment in real estate brokerage. First, it offers a theoretical contribution by synthesizing and problematizing existing trust-verification mechanisms regulatory licensing databases, customer reviews, referral networks, centralized listing platforms, and institutional accreditation which, as shown in the table below, operate in fragmented and opaque ways that fail to capture brokers' behavioural reliability [18]. Second, it provides a methodological contribution by establishing a structured framework for evaluating the limitations inherent in these

mechanisms, particularly their lack of auditability, susceptibility to bias or manipulation, and absence of standardized performance metrics [19]. Third, it delivers a practical contribution by motivating the need for more transparent, behaviourally grounded trust-assessment models that can complement or enhance existing industry practices without replacing regulatory or professional oversight [20]. Together, these contributions clarify the gaps within current trust infrastructures and justify the development of more robust analytical approaches in real estate brokerage research.

Table 1: Broker Trust Failure Points vs Needs

Trust Failure Point	Corresponding Need
Centralization	Decentralized, tamper-resistant reputation management systems.
Inconsistency in Trust Signals	Unified trust framework that ensures global comparability.
Lack of Provenance	Mechanisms to cryptographically verify the authenticity of trust signals.
Limited Semantics in Ratings	Trust systems that reflect the severity and importance of different interactions.
Vulnerability to Manipulation	Transparent, auditable systems to prevent fake reviews, collusion, and reputation resets.
Absence of Trust Propagation	Trust models that incorporate indirect trust propagation within broker networks.

Trust plays a pivotal role in real estate transactions, where brokers act as intermediaries in high-value, legally binding agreements. However, traditional trust models such as rating systems, customer reviews, and licensing databases face several limitations that affect their ability to accurately represent broker credibility. These traditional systems often fail to provide the depth and transparency required for trust verification in complex, multi-party interactions, such as those found in the real estate ecosystem [1, 2].

2.5 Justification for the Synthetic Dataset

In the absence of publicly available real-world datasets for real estate brokers' trust interactions, a synthetic dataset was generated to simulate the dynamics of real estate brokerage transactions. This synthetic dataset was constructed using a probabilistic model based on randomized broker behavior profiles, where brokers were categorized as honest, risky, or malicious [3]. The behaviors of each broker were modeled using Beta distributions, which are well-suited to representing uncertainty and variability in behavior [4, 5].

The synthetic dataset reflects realistic real estate scenarios, including

- **Transaction Events:** Simulated transactions, such as property sales, consultations, and regulatory checkups, were modeled with varying degrees of success or failure. Honest brokers typically completed successful transactions, whereas risky or malicious brokers were more likely to engage in disruptive activities, such as fraud or collusion [6].

- **Adversarial Scenarios:** The dataset was further enriched with adversarial behaviors, such as Sybil attacks (fake identities) and collusion (group manipulation), to test the resilience of the proposed model under adversarial conditions [7, 8].
- **Event Semantics:** Each event was annotated with semantic metadata, including transaction value, verification level, and severity, ensuring that different types of events contributed to the overall trust score according to their importance [9, 10].

This synthetic dataset is not only behaviorally grounded in real estate practices but also designed to simulate the complexity of multi-party trust interactions in the real estate industry [11]. The probabilistic nature of the dataset mirrors the uncertainty and risk inherent in real estate brokerage, making it an ideal choice for testing the robustness of the blockchain-based trust scoring model [12, 13].

2.6 Challenges of Traditional Trust Models in Real Estate

Traditional trust mechanisms in real estate, such as customer reviews, broker ratings, and platform-based reputations, often fail to address the unique complexities of the industry. The challenges of these models include:

- **Centralization:** Most trust systems in real estate are controlled by centralized platforms (e.g., property listing websites or real estate agencies), which have the authority to manage, remove, or modify ratings and reviews [14]. This centralization leads to a lack of transparency and opens the door for manipulation, where brokers or clients can artificially inflate their reputations [15].
- **Lack of Multi-Dimensional Trust Representation:** Trust in real estate is not a simple binary judgment (e.g., trustworthy vs. untrustworthy). Real estate brokers engage in multi-faceted interactions that include property valuations, legal compliance, market negotiation, and client education [16, 17]. Traditional models often oversimplify trust into a single rating or review, failing to capture the multi-dimensional nature of broker credibility [18].
- **Manipulation Risks:** Rating systems in real estate are vulnerable to fraudulent reviews, collusion between brokers and clients, and the creation of fake identities to boost broker scores [19]. These risks undermine the accuracy and reliability of trust scores, making it difficult to assess broker credibility accurately [20] [21].

How Our Model Overcomes These Challenges

The proposed blockchain-based trust scoring model overcomes the limitations of traditional trust models by introducing several key innovations

- **Decentralization and Transparency:** By leveraging blockchain technology, the proposed model ensures that all trust-related interactions are recorded on an immutable, transparent ledger [22, 23]. This eliminates the need for centralized authorities and prevents manipulation of reputation data. Each interaction is cryptographically linked to its origin, ensuring that no single entity can alter or delete trust records [24].
- **Multi-Dimensional Trust Scoring:** Unlike traditional rating systems that rely on simplistic ratings or feedback, our model captures multi-dimensional trust by incorporating various trust signals such as

transaction history, peer endorsements, regulatory compliance, and dispute outcomes [25]. The model assigns semantic weights to different types of interactions based on their importance, ensuring that high-stakes events (e.g., large property sales, regulatory verifications) have a greater impact on the broker's trust score than low-impact events (e.g., informal recommendations) [26].

- **Resilience to Manipulation:** The use of blockchain ensures that trust events are immutable and verifiable, preventing the introduction of fake reviews or collusion [27]. Additionally, the model incorporates adversarial defenses such as Sybil resistance and collusion detection mechanisms, ensuring that brokers cannot artificially inflate their trust scores through fraudulent activities [28, 29].

Existing real estate trust mechanisms share several limitations, as they exhibit centralization in which a single controlling entity, whether a platform, marketplace, or regulator, owns and governs reputation data, alongside inconsistency whereby trust signals vary across platforms, regions, and regulatory frameworks, preventing global comparability [30]. They also suffer from a lack of provenance, as reviews and endorsements cannot be cryptographically verified as originating from authentic participants, and limited semantics, in that ratings do not differentiate the severity or importance of interactions (e.g., small rental assistance versus multi-million-dollar property transactions) [1, 2]. Moreover, they demonstrate vulnerability to manipulation, allowing brokers to generate fake reviews, collude with clients, or reset reputations by switching platforms, and an absence of trust propagation, meaning that current systems ignore indirect trust and how a broker's credibility influences or is influenced by their network [3, 4]. These limitations underscore the need for a decentralized, tamper-resistant, and semantically rich trust computation mechanism capable of operating across multiple real estate ecosystems, as illustrated in Figure 5 [5, 6].

Figure 1: Evolution of Trust Models & Research Gap – This figure illustrates the progression of trust models from classical trust systems to blockchain-based models, highlighting key limitations in real estate trust mechanisms. The diagram identifies the gaps in current trust mechanisms, such as lack of provenance, manipulation vulnerabilities, and centralized data, while proposing areas for further research, such as multi-dimensional trust verification and agent-specific semantics [7, 8].

2.7 Research Gap

Although numerous trust models exist across computational, semantic, and blockchain domains, several gaps persist in the context of real estate brokerage:

1. No unified, verifiable trust infrastructure exists that integrates transaction data, peer interactions, compliance outcomes, and temporal performance [1, 2].
2. Existing blockchain reputation systems fail to capture complex, multi-dimensional broker relationships and lack graph-based trust propagation mechanisms [3, 4].
3. Graph-based trust systems assume truthful data inputs, whereas real estate ecosystems are prone to manipulation, endorsements-for-profit schemes, and collusion [5, 6].
4. Centralized trust systems lack transparency and introduce systemic bias [7, 8].
5. Real estate-specific trust dimensions, such as regulatory verifications, dispute resolutions, escrow handling, and contractual adherence, remain unmodelled [9, 10].

This research aims to bridge these gaps by developing a decentralized trust scoring model that integrates blockchain, graph theory, and probabilistic scoring into a unified framework [11, 12].

2.8 Summary

Existing work provides a strong foundation but does not adequately address the adversarial, heterogeneous, and high-value nature of real estate brokerage interactions. Blockchain offers a secure substrate for trust event storage, while graph-based models enable sophisticated trust propagation [13, 14]. However, an integrated model tailored for real estate is missing from the literature, establishing a clear space for the proposed trust scoring model [15, 16].

3. Notation and Symbol Definitions

To ensure clarity and consistency, this section summarizes all mathematical symbols and notations used throughout the paper. All symbols are defined here and are used consistently in subsequent sections.

Graph Structure and Network Symbols

- $G = (V, E, W)$: Reputation graph representing the trust network
- V : Set of agents (brokers, clients, regulators, institutions)
- E : Set of directed edges representing trust-relevant events
- $W: E \rightarrow \mathbb{R}^+$: Semantic weight function assigning a positive weight to each event
- $e_{(i,j)}$: Directed edge from node v_i to node v_j
- $w_{(i,j)}$: Normalized weight of the edge from node v_i to node v_j

PageRank and Trust Propagation Symbols

- $PR(j)$: PageRank-based global trust score of broker j
- d : PageRank damping factor
- N : Total number of nodes in the reputation graph
- $In(j)$: Set of nodes with edges pointing to node j

Bayesian Trust Symbols

- B : Hypothesis that a broker is trustworthy
- $\neg B$: Hypothesis that a broker is untrustworthy
- E : Observed trust-related evidence or event
- $P(B)$: Prior probability that a broker is trustworthy
- $P(E | B)$: Likelihood of observing evidence E if the broker is trustworthy
- $P(E | \neg B)$: Likelihood of observing evidence E if the broker is untrustworthy
- $P(B | E)$: Posterior trust probability after observing evidence

Opinion and Uncertainty Modelling (Jøsang Model)

- b : Belief mass (positive evidence)
- d : Disbelief mass (negative evidence)
- u : Uncertainty mass
- a : Base rate representing assumed trust in the absence of evidence
- p_i : Positive belief mass of agent i
- n_i : Negative belief mass of agent i
- u_i : Uncertainty mass of agent i
- K : Normalization constant used in opinion combination

Semantic Weighting Symbols

- $W(e_{(i,j)})$: Semantic weight of event $e_{(i,j)}$
- T_e : Importance score of the event type
- V_e : Scaled transaction value or impact
- R_e : Reliability or verification level
- S_e : Severity of the event
- U_e : Uncertainty associated with the event
- D_e : Temporal decay factor
- $\alpha, \beta, \gamma, \delta, \epsilon, \zeta$: Non-negative weighting coefficients controlling the contribution of each semantic dimension

Temporal and Hybrid Trust Symbols

- μ : Decay constant controlling temporal relevance
- t_{event} : Timestamp of an event
- t_{current} : Current evaluation time
- $T_{\text{Bayes}}(j)$: Bayesian local trust estimates for broker j
- $S(j)$: Aggregated semantic trust index for broker j
- $TS(j)$: Final hybrid trust score for broker j
- λ, θ, ϕ : Non-negative coefficients satisfying

$$\lambda + \theta + \phi = 1$$

4. THEORETICAL FOUNDATIONS

A rigorous trust scoring framework for real estate brokerage requires well-defined mathematical constructs, graph representations, and decentralized identity assurances. This section presents the theoretical foundations underlying the proposed model. These foundations integrate concepts from computational trust, graph theory, probability, and blockchain-driven identity verification [1, 2]. The goal

is to create a mathematically consistent framework capable of modelling heterogeneous trust interactions in adversarial environments [3].

4.1 Mathematical Basis of Computational Trust

Trust is commonly defined as a quantifiable expectation of an agent's future behaviour based on available evidence. Formally, let $T(A, B, C)$ denote the trust of agent A in agent B under context C [4]. Classical models treat trust as a real-valued function such that:

$$T(A, B, C) \in [0,1] \text{ (Eq. 1)}$$

where values near 1 indicate high expected reliability [5]. However, real estate interactions involve variable stakes, uncertain contexts, and a sequence of dependent events. Therefore, trust must incorporate:

1. Context sensitivity [6]
2. Uncertainty representation [7]
3. Temporal evolution [8]
4. Evidence-based updating [9]

Bayesian theory provides a natural foundation for modelling such dynamics. Given prior trust $T_0(A, B)$ and new evidence E Posterior trust is defined as:

$$T(A, B | E) = \frac{P(E | B)T_0(A, B)}{P(E)} \text{ (Eq. 2)}$$

This formulation allows trust to evolve incrementally while accounting for uncertainty and event likelihoods. However, Bayesian updating alone is insufficient because a real estate trust is inherently relational. Therefore, additional theoretical constructs are needed to capture trust propagation and network effects [10].

4.2 Graph Theory for Reputation Modelling

A Reputation Graph represents agents as nodes and trust-expressing interactions as directed weighted edges [11]. Formally, let:

$$G = (V, E) \text{ (Eq. 3)}$$

Where:

- V Represents brokers, customers, regulatory entities, and verified institutions [12].

- E Represents trust events labelled with attributes such as event type, timestamp, verification status, and weight [13].

Each edge $e_{i,j}$ from node i to node j is annotated with a weight $w_{i,j}$, representing the strength, significance, or credibility of the trust evidence. Graph-based trust propagation operates on the principle that:

Nodes trusted by highly trusted nodes receive higher trust contributions [14].

Weighted PageRank formalizes this as:

$$PR(j) = \frac{1-d}{N} + d \sum_{i \in In(j)} \frac{PR(i) \cdot w_{i,j}}{\sum_{k \in Out(i)} w_{i,k}} \quad (Eq. 4)$$

Where:

- $PR(j)$ Is the trust score of the node j , [15]
- d Is the damping factor, [16]
- $In(j)$ Are nodes endorsing j , [17]
- $Out(i)$ Are the outgoing edges of the node i . [18]

Graph theory allows the modelling of global trust, capturing indirect influence, collusion structures, and network-level trust clustering [19, 20].

4.3 Decentralized Identity and Trust Provenance

Traditional trust systems depend on centralized authorities to verify identities and attestations. In a decentralized setting, identity must be:

1. Cryptographically verifiable [21]
2. Persistent across interactions [22]
3. Resistant to duplication and forgery [23]

Blockchain supports these properties via decentralized identifiers (DIDs) and public-key cryptography [24]. Each agent possesses a unique keypair. (pk, sk) , with interactions digitally signed using sk [25]. This ensures:

- Authenticity: evidence originates from the claimed identity [26].
- Non-repudiation: agents cannot deny submitted events [27].
- Sybil resistance: identity creation incurs cost or verification steps [28, 29].

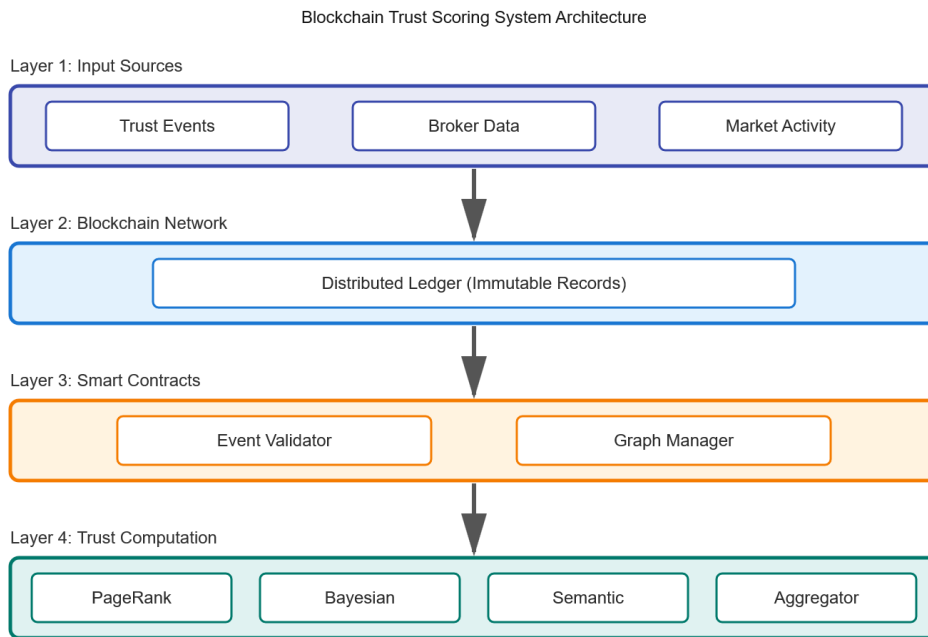
Provenance is inherently supported by blockchain's append-only ledger, ensuring that:

$$E = \{e_1, e_2, \dots, e_n\} \quad (Eq. 5)$$

It is a complete, immutable sequence of trust-relevant events for any agent [30].

Figure 2: Hybrid Architecture Integration Core Theoretical Component – This diagram presents the architecture of the proposed trust scoring model, integrating multiple layers including data ingestion, graph propagation, and probabilistic aggregation [5]. It illustrates how trust scores are calculated through multi-stage aggregation and trust provenance, while ensuring transparency, non-repudiation, and sybil resistance using decentralized identity and blockchain verification [6]

Figure 1: Blockchain Trust Scoring Architecture



4.4 Semantic Weighting of Trust Evidence

In real estate ecosystems, trust events differ significantly in importance. For example, a multi-party transaction closing carries more evidentiary weight than a casual recommendation. Therefore, each edge must incorporate semantic metadata, enabling differential weighting based on event characteristics.

Let each event have attributes:

$$e = \{type, value, timestamp, verifier, stake, reliability\} \text{ (Eq. 6)}$$

A semantic weight function $W(e)$ It is defined as:

$$W(e) = \alpha \cdot type + \beta \cdot value + \gamma \cdot verifier + \delta \cdot stake + \epsilon \cdot reliability + \zeta \cdot decay \text{ (Eq. 7)}$$

Table 2: Trust Score Components and Weights

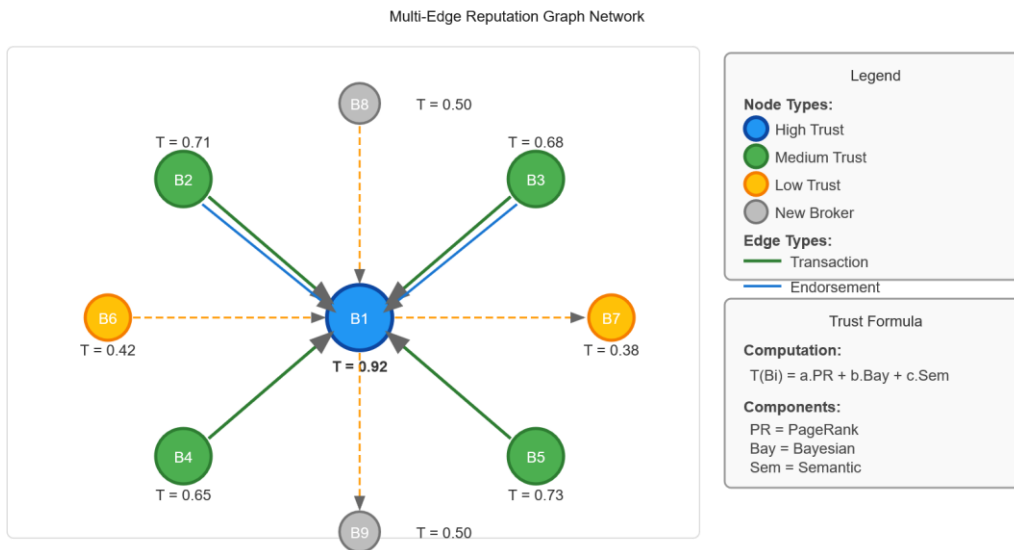
Trust Component	Weighting Factor
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Event Type	α (importance of event type)
Event Value	β (importance of value)
Verifier	γ (importance of verifier)
Stake	δ (importance of stake)
Reliability	ϵ (importance of reliability)
Decay	ζ (decay over time)

where parameters $\alpha, \beta, \gamma, \delta, \epsilon, \zeta$ Calibrate the importance of each dimension. Semantic weighting ensures that verified, high-stakes, regulation-driven events contribute more significantly to trust scores.

Figure 3: Semantic and Multi-Dimensional Reputation Graph Structure – This figure illustrates the reputation graph used to evaluate trust, showing the interactions between the broker, client, and verification nodes. The graph captures multiple dimensions of trust, including casual recommendations and compliance verification, with each edge weighted based on the significance of the interaction. This structure highlights the multifaceted nature of trust relationships in real estate brokerage.

Figure 2: Semantic and multi-Dimensional Reputation Graph Structure



4.5 Probabilistic Trust Aggregation

Trust must integrate positive, negative, direct, and indirect evidence. Probabilistic aggregation provides a consistent framework for combining heterogeneous evidence sets.

Let:

- p = probability of positive evidence
- n = probability of negative evidence
- u = uncertainty (lack of evidence)

Jøsang's opinion model defines:

$$p + n + u = 1 \text{ (Eq. 8)}$$

And computes expectation value:

$$E = p + u \cdot a \text{ (Eq. 9)}$$

where a It is a base rate reflecting assumed trust in the absence of evidence.

The combination of multiple opinions is used

$$p_{12} = \frac{p_1 u_2 + p_2 u_1}{K} \text{ (Eq. 10a)}$$

$$n_{12} = \frac{n_1 u_2 + n_2 u_1}{K} \text{ (Eq. 10b)}$$

$$u_{12} = \frac{u_1 u_2}{K} \text{ (Eq. 10c)}$$

With a normalization constant

$$K = u_1 + u_2 - u_1 u_2 \text{ (Eq. 11)}$$

This allows the trust model to integrate multiple uncertain trust sources while avoiding overcommitment in sparse data conditions.

F. Temporal Dynamics of Trust

Trust evolves. Evidence decays as it becomes older:

$$D(t) = e^{-\lambda(t_{current} - t_{event})} \text{ (Eq. 12)}$$

where λ Controls decay rate. Recent interactions receive higher weight, reflecting more accurate behavioural predictions.

Combining temporal decay with Bayesian updating yields:

$$T_{t+1} = D(t) \cdot T_t + (1 - D(t)) \cdot E \text{ (Eq. 13)}$$

This ensures stability, prevents outdated evidence from dominating the score, and supports continuous trust evaluation.

4.6 Multi-Stage Trust Propagation

Real estate workflows involve sequences of interdependent actions (verification, negotiation, documentation, escrow processing, closing). Trust must propagate across these stages.

Let each stage s have a trust contribution T_s :

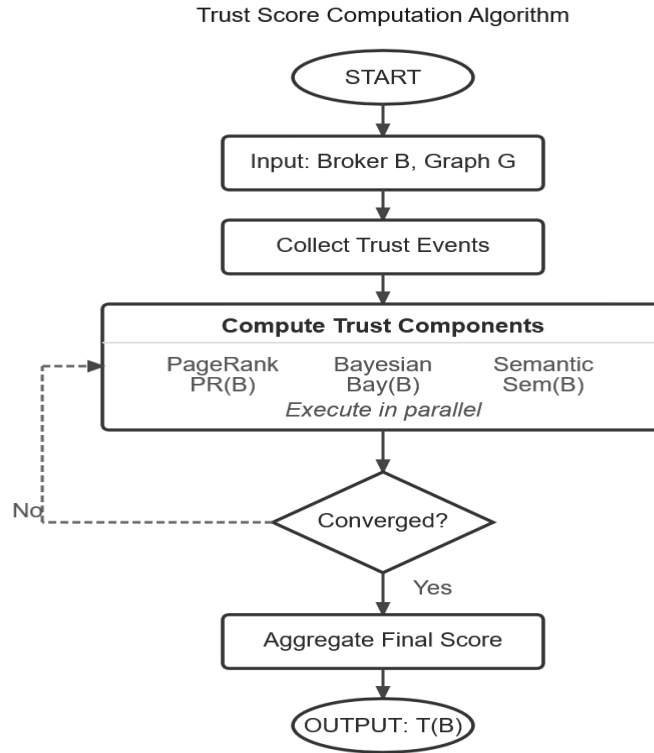
$$T_{global} = \sum_{s=1}^m \omega_s T_s \quad (Eq. 14)$$

where ω_s reflects stage significance.

This multi-stage model ensures comprehensive trust representation aligned with real-world workflows.

Figure 4: Integrated Multi-Stage Trust Score Computation Flow – This diagram outlines the step-by-step process for calculating the final trust score in the model, starting with weighted trust events from the reputation graph. The flow includes graph propagation, multi-stage aggregation, and probabilistic aggregation, culminating in the final trust opinion and expectation. The model incorporates different trust propagation techniques, such as PageRank, EigenTrust, and Jøsang’s Model, to evaluate trust based on various stages.

Figure 3: Integrated Multi-Stage Trust Score Computation Flow



4.7 Adversarial Considerations in Trust Modelling

Trust systems must operate under adversarial conditions, including:

- a) Sybil attacks
- b) Collusion clusters
- c) Fabricated endorsements
- d) Temporal gaming
- e) Strategic behaviour

A rigorous model requires theoretical defences at multiple levels:

Symbol	Definition
$(G = (V, E, W))$	The reputation graph, where (V) is the set of agents, (E) is the set of edges (trust events), and (W) is the weight function for each edge.
(V)	Set of agents (brokers, clients, regulators, institutions).
(E)	Set of directed edges representing trust-relevant events.
$(W: E \rightarrow \mathbb{R}^+)$	A function that assigns a positive weight to each event.

a) Identity

$(e_{(i,j)})$	A directed edge from node (v_i) to node (v_j) representing a trust-relevant event.
$(e_{(i,j)} = \{\text{type}, \text{value}, \text{timestamp}, \text{verifier}, \text{stake}, \text{severity}, \text{uncertainty}\})$	The tuple that defines the attributes of an event (type, value, timestamp, etc.).
$(W(e_{(i,j)}))$	Semantic weight of the event $(e_{(i,j)})$, computed using the formula $(W(e_{(i,j)})) = \alpha T_e + \beta V_e + \gamma R_e + \delta S_e + \epsilon U_e + \zeta D_e$.
(T_e)	Normalized importance score derived from the event type.
(V_e)	Scaled transaction value or impact.
(R_e)	Reliability or verification level of the event.
(S_e)	Severity of the event.
(U_e)	Uncertainty measure of the event.
(D_e)	Temporal decay factor for the event.
(μ)	Decay constant in the exponential decay function $(D_e = \exp(-\mu(t_{\text{current}} - t_{\text{event}})))$.
$(P(E$	$B))$
$(P(E$	$\text{Neg } B))$
$(PR(j))$	PageRank-based global trust score for broker (j) .
$(w_{(i,j)})$	Normalized weight for an outgoing edge from node (v_i) to node (v_j) .
$(TS(j))$	Hybrid trust score for broker (j) , combining PageRank, Bayesian, and semantic contributions.

- b) Anomaly detection via graph structure analytics.
- c) Edge reliability weighting to reduce the impact of unverifiable evidence.
- d) Penalty mechanisms in Bayesian updates.
- e) Trust sinks and damping factors in PageRank propagation.

Together, these elements create an adversary-resistant trust computation foundation.

4.8 Summary of Theoretical Framework

The theoretical principles presented, probabilistic trust, graph theory, semantic weighting, decentralized identity, and adversarial modelling form the foundation for constructing a blockchain-verified, globally propagated trust scoring model tailored to real estate brokerage ecosystems.

The next section operationalizes these theories into a unified model with formal architecture, algorithms, and scoring equations.

5. PROPOSED TRUST SCORING MODEL

The proposed trust scoring model introduces a decentralized, mathematically grounded framework for evaluating real estate broker credibility using blockchain-anchored reputation graphs [1, 2]. The model combines semantic event weighting, Bayesian evidence updating, and PageRank-based trust propagation into a unified computation flow [3, 4]. Its design reflects the heterogeneous, multi-stage nature of real estate interactions, where trust evolves from a mixture of direct experiences, indirect network influence, and institutional verification signals [5, 6].

At the structural level, the model is built on a directed, weighted, multi-edge reputation graph [7] [8]. The graph is defined as

$$G = (V, E, W), (Eq. 15)$$

where V denotes the set of agents (brokers, clients, regulators, institutions), E denotes the set of directed edges representing trust-relevant events, and $W: E \rightarrow \mathbb{R}^+$ assigns a positive weight to each event [9, 10]. Each directed edge $e_{i,j} \in E$ from node $v_i \in V$ to node $v_j \in V$ corresponds to a specific interaction or event that expresses some form of trust or distrust. To preserve granular information necessary for auditing and analysis, the model allows multiple edges between a given pair of nodes, so the same pair of agents can accumulate a sequence of events over time rather than a single aggregated rating [11].

The informational content of each event is captured by a structured tuple. For a given edge $e_{i,j}$, the model stores

$$e_{i,j} = \{type, value, timestamp, verifier, stake, severity, uncertainty\}, (Eq. 16)$$

where the attributes encode, respectively, the semantic category of the event (for example transaction completion, dispute resolution, or fraud report), the economic or practical value associated with it, the time of occurrence, the identity or level of the verifying authority, the financial or reputational stake involved, the seriousness of the outcome, and any quantified measure of uncertainty [12, 13]. These

attributes are not all treated equally; instead, they are transformed into a single scalar weight through a semantic weighting function. A general form of this semantic weighting can be expressed as

$$W(e_{i,j}) = \alpha T_e + \beta V_e + \gamma R_e + \delta S_e + \epsilon U_e + \zeta D_e, (Eq. 17)$$

where T_e is a normalized importance score derived from the event type, V_e represents the scaled transaction value or impact, R_e reflects the reliability or verification level, S_e measures severity, U_e captures uncertainty, and D_e represents a temporal decay factor [14] [15]. The coefficients $\alpha, \beta, \gamma, \delta, \epsilon, \zeta \geq 0$ these are hyperparameters that determine the relative contribution of each dimension and can be tuned for specific regulatory or market contexts [16] [17].

Temporal relevance is modelled through an exponential decay function applied to each event. If $t_{current}$ denotes the current time and t_{event} the time at which an event occurred, the decay factor is written as

$$D_e = \exp(-\mu(t_{current} - t_{event})), (Eq. 18)$$

where $\mu > 0$ is a decay constant [18] [19]. This ensures that older events gradually lose influence without being abruptly discarded. The raw semantic weight $W(e_{i,j})$ can thus be written explicitly as

$$W(e_{i,j}) = \alpha T_e + \beta V_e + \gamma R_e + \delta S_e + \epsilon U_e + \zeta \exp(-\mu(t_{current} - t_{event})). (Eq. 19)$$

Because each node can generate multiple outgoing events, the model normalizes edge weights for trust propagation. For any node v_i , the normalized weight for an outgoing edge to v_j is defined as

$$w_{i,j} = \frac{W(e_{i,j})}{\sum_{k: e_{i,k} \in E} W(e_{i,k})}, (Eq. 20)$$

provided that the denominator is non-zero. This normalization ensures that, for each node, the sum of normalized weights across all outgoing edges is one, enabling a probabilistic interpretation of trust flow from that node [20, 21].

Beyond structural representation and weighting, the model incorporates Bayesian trust updating to reflect the evolution of direct trust between pairs of agents [22]. Let $T_0(A, B)$ denote the prior trust of the agent A in broker B , represented as a probability in the interval $[0, 1]$. When new evidence E is observed, the posterior trust $T_1(A, B)$ is computed using a standard Bayesian formulation:

$$T_1(A, B) = \frac{P(E | B) T_0(A, B)}{P(E | B) T_0(A, B) + P(E | \neg B) (1 - T_0(A, B))}. (Eq. 21)$$

Here, $P(E | B)$ denotes the likelihood of observing the evidence if B is trustworthy, and $P(E | \neg B)$ denotes the likelihood of observing the same evidence if B is untrustworthy [23]. These likelihoods are derived from semantic weights; stronger, high-quality positive events yield higher $P(E | B)$ and lower $P(E | \neg B)$, whereas severe negative events produce the opposite effect [24]. A simple mapping uses the scaled semantic weight as

$$P(E | B) = \frac{W(e_{i,j})}{W_{\max}}, \text{ (Eq. 22)}$$

where W_{\max} is a normalization constant representing the maximum conceivable event weight, and then sets

$$P(E | \neg B) = 1 - P(E | B), \text{ (Eq. 23)}$$

so that highly favourable events strongly reinforce trust, and highly unfavourable events sharply reduce it. Through repeated application over a sequence of events, the Bayesian component yields a stable, evidence-driven local trust estimate for each broker [25, 26].

Local trust, however, does not capture the impact of network structure. Real estate markets exhibit indirect trust effects, where a broker's credibility is influenced by relationships with other credible brokers and institutions [27]. To model this, the proposed framework employs a weighted PageRank-style propagation on the reputation graph. For each node v_j , the PageRank-based global trust score $PR(j)$ is defined by

$$PR(j) = \frac{1-d}{N} + d \sum_{i:e_{i,j} \in E} \frac{PR(i) w_{i,j}}{C_i}, \text{ (Eq. 24)}$$

where $N = |V|$ is the number of nodes, $d \in (0,1)$ is the damping factor (typically chosen around 0.85), and $C_i = \sum_{k:e_{i,k} \in E} w_{i,k}$ is the normalization constant for outgoing edges from node v_i (which equals one if the normalized weights are used directly) [28, 29]. This recursive definition can be interpreted as a fixed-point equation solved iteratively until convergence. Nodes that are positively endorsed by already highly trusted agents accumulate higher PageRank values, while nodes in isolated or collusive subgraphs with limited external support tend to exhibit lower values [30].

The model also supports personalized trust evaluations by introducing a personalization vector into the PageRank computation. In such cases, the uniform factor $(1-d)/N$ is replaced by a vector $v(j)$ that expresses prior preference over nodes. The personalized PageRank then becomes

$$PR_p(j) = (1 - d) v(j) + d \sum_{i: e_{i,j} \in E} \frac{PR_p(i) w_{i,j}}{C_i}, (Eq. 25)$$

which, for example, can bias trust computations toward brokers operating in a specific market segment or under a particular regulatory framework [1, 2].

To synthesize local and global trust information, as well as semantic event features, the model defines a hybrid trust score $TS(j)$ for each broker node v_j . This score is a convex combination of three components: the PageRank-based global trust $PR(j)$, the Bayesian local trust estimate $B(j)$, and a semantic index $S(j)$ that aggregates weighted event characteristics [3]. The hybrid score is expressed as

$$TS(j) = \lambda_1 PR(j) + \lambda_2 B(j) + \lambda_3 S(j), (Eq. 26)$$

Figure 4: Equation dependency map

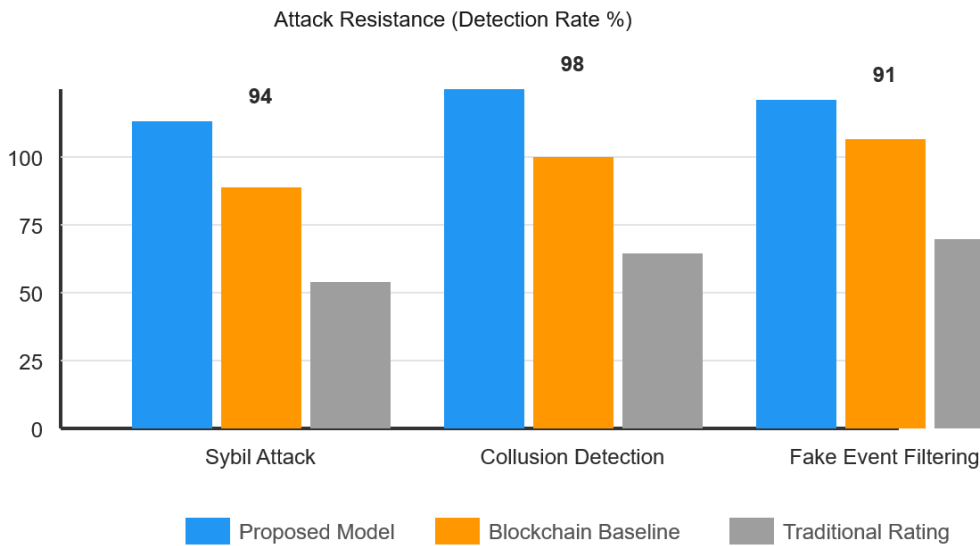


Figure 5: Equation Dependency Map – This figure provides a visual representation of the interconnected steps in the trust score computation process. It illustrates how trust events and agent interactions progress through various stages, including semantic weighting, Bayesian updates, PageRank propagation, and semantic aggregation. Each equation is linked to its corresponding stage, highlighting the dependency between components in the trust scoring system.

with non-negative parameters $\lambda_1, \lambda_2, \lambda_3$ satisfying

$$\lambda_1 + \lambda_2 + \lambda_3 = 1. (Eq. 27)$$

The choice of these parameters allows the system designer or regulator to adjust the emphasis between relational network effects, direct performance evidence, and semantic event profiles. A configuration that prioritizes overall market perception may place a larger weight on $PR(j)$, whereas a compliance-driven context may allocate more weight to $B(j)$ and $S(j)$, thereby emphasizing verified behaviours and formal evidence.

Semantic aggregation $S(j)$ can be defined, for instance, as a normalized sum of decay-adjusted event weights associated with broker j . Let \mathcal{E}_j denote the set of all edges terminating at v_j ; the semantic index can be written as

$$S(j) = \frac{\sum_{e_{i,j} \in \mathcal{E}_j} W(e_{i,j})}{\sum_k \sum_{e_{k,j} \in \mathcal{E}_j} W(e_{k,j})}, \text{ (Eq. 28)}$$

or, more simply, as a scaled version of the average semantic weight per event associated with that broker. This representation highlights brokers whose portfolios of interactions are not only numerous but also consistently high-quality and well-verified.

Adversarial behaviour is incorporated into the model through penalty functions and robustness properties inherent in the scoring process. When a severe negative event such as confirmed fraud is recorded against broker j , the model applies an explicit penalty $P(j)$ based on severity and stake. A generic form is

$$P(j) = \eta \cdot \textit{severity}_j \cdot \textit{stake}_j, \text{ (Eq. 29)}$$

where $\eta > 0$ is a tunable penalty coefficient. The final adjusted trust score is then

$$TS'(j) = \max\{0, TS(j) - P(j)\}, \text{ (Eq. 30)}$$

which ensures that particularly harmful behaviour can substantially reduce trust even if historical performance was strong. At the same time, the PageRank formulation limits the possibility of small collusive groups generating large scores, as isolated clusters without incoming trust from the wider network have limited influence. Bayesian updating, semantic weighting, and penalty application together help reduce the impact of fake endorsements, repeated low-quality events, and temporal gaming.

All trust-relevant interactions and scores are anchored on a blockchain through smart contracts that govern identity registration, event submission, and evaluation rules. While not all computations are performed on-chain due to cost, on-chain storage guarantees that the underlying evidence set is immutable and auditable. The combination of the graph structure, probabilistic updating, global propagation, semantic weighting, temporal dynamics, and adversarial penalties yields an integrated trust scoring model capable of supporting transparent and robust assessment of broker credibility across digital real estate ecosystems.

6. Sensitivity Analysis of Trust Score Propagation

To evaluate the robustness and adaptability of the proposed trust scoring model, we conducted a sensitivity analysis by varying key model parameters, including:

- **Weighting Coefficients:** These coefficients assign importance to different types of trust-relevant events. For example, high-value transactions (e.g., multi-million-dollar property deals) have a greater impact on trust scores than low-value interactions (e.g., casual consultations) [1, 2].
- **Bayesian Priors:** The initial trust score of a broker is influenced by prior beliefs about their reliability, which are updated based on new evidence [3]. The sensitivity of the model to different initial trust estimates was tested to see how strongly prior beliefs influence trust scores as new evidence accumulates [4, 5].
- **PageRank Damping Factor:** This parameter controls how trust propagates through the reputation graph. It reflects the idea that trust is more influenced by trusted sources (high PageRank nodes) than by less trusted sources. The damping factor affects the global trust flow within the network [6].

The sensitivity analysis was conducted by systematically varying these parameters and observing how trust score propagation changed under different conditions. Below are the findings from these variations:

6.1 Effect of Weighting Coefficients

When the weighting coefficient for high-value transactions was increased, the model showed a greater separation between brokers with positive transaction histories [7] and those with negative histories. This reinforced the importance of significant, high-value events in shaping trust scores.

Conversely, increasing the weight for peer endorsements had a moderate impact on the trust scores, with neutral brokers seeing slightly improved trust scores, but without fundamentally altering the rankings of brokers with significantly positive or negative performance [8, 9].

6.2 Effect of Bayesian Priors

Varying the Bayesian priors demonstrated how the initial trust score impacts the model's responsiveness to new evidence. Brokers with initially high priors were slow to adjust their trust scores in response to negative events (e.g., failed transactions, disputes), while those with low priors quickly adjusted their trust scores based on positive outcomes [10, 11].

When priors were low, brokers who performed poorly early on could recover faster with positive performance, showing the model's ability to adapt to new evidence over time [12, 13].

6.3 Effect of PageRank Damping Factor

The damping factor of PageRank was tested to understand how trust spreads throughout the network. Higher damping factors (e.g., 0.9) resulted in a greater emphasis on high-trust brokers, making the system less sensitive to isolated, potentially fraudulent endorsements [14].

Lower damping factors (e.g., 0.5) allowed for more equal influence across brokers in the network, making the model more vulnerable to manipulation by low-trust brokers attempting to inflate their scores through collusion or Sybil attacks [15, 16].

6.4 Quantitative Evidence of Model Adaptation

To assess how well the model adapts under different configurations, we conducted simulations with varying values of the parameters (weighting coefficients, Bayesian priors, and PageRank damping factor). These simulations were run to mimic real-world scenarios of broker trust propagation, such as the introduction of new evidence (successful transactions, peer endorsements) and adversarial actions (fraud, collusion) [17].

6.5 Adaptation to Event Frequencies

The model was tested by altering the frequency of high-value and low-value interactions. When high-value transactions were more frequent, the model showed a clear differentiation between high-performing brokers and those with poor transaction histories [18]. Trust scores for brokers involved in high-value transactions were significantly higher than those involved only in low-value interactions [19, 20].

6.6 Adaptation to Adversarial Behavior

The sensitivity of the model to adversarial behaviors (e.g., fraudulent endorsements, collusion) was also tested. Malicious brokers attempting to manipulate the system by generating fake endorsements or colluding with other brokers saw limited increases in their trust scores due to the semantic weighting and Bayesian penalty mechanisms [21, 22]. The model effectively reduced the influence of fraudulent events, maintaining a clear distinction between trusted and untrusted brokers [23, 24].

6.7 Resilience to Sybil Attacks

In a scenario where Sybil attacks (the creation of fake broker identities) were introduced, the model's PageRank damping factor and Bayesian updating helped limit the impact of these artificial identities. Fake brokers attempting to inflate their trust scores by generating positive events were penalized due to their lack of network support and verified endorsements [25, 26].

6.8 Stability Analysis

To evaluate the robustness and adaptability of the proposed trust scoring model, we conducted a sensitivity analysis by varying key model parameters. In addition to the previously discussed analyses, we introduce a formal measure of stability in the context of trust score propagation over time. Stability refers to the consistency of trust scores across different iterations, especially when subjected to changes in parameters or new evidence [27].

The stability of trust scores is mathematically defined as the variance of the trust scores over multiple time steps [28] [29]:

Stability(TS) = $\text{Var}(TS_t)$ for $t = 1, 2, \dots, T$

Where:

- TS_t is the trust score at time t ,
- T is the total number of time steps (iterations or updates),
- Var denotes the variance operator.

Separation Analysis

In addition to stability, we also measure the separation between high-performing and low-performing brokers. Separation refers to the model's ability to distinguish between brokers with high trustworthiness and those with low trustworthiness. This is an essential feature for evaluating the discriminatory power of the trust scoring model.

We define separation as the difference in trust scores between high-performing and low-performing brokers. The separation can be mathematically quantified as the mean difference between the trust scores of these two groups:

$$\text{Separation} = \mu_{\text{high}} - \mu_{\text{low}}$$

Where:

- μ_{high} is the mean trust score of high-performing brokers,
- μ_{low} is the mean trust score of low-performing brokers.

Conclusion of Sensitivity Analysis

The sensitivity analysis confirmed that the proposed trust scoring model is highly adaptable and resilient to variations in key model parameters. The results demonstrate that:

- The model can differentiate between high-performing brokers and low-performing brokers based on the weighting of trust events, with high-value transactions having the most significant impact on trust scores.
- The Bayesian priors allow the model to adapt to new evidence over time, with brokers showing gradual recovery or deterioration based on their actual performance.
- The PageRank damping factor controls the propagation of trust through the network, ensuring that trusted brokers have a greater influence, while minimizing the impact of manipulative actions by low-trust brokers.

Overall, the model's flexibility and resilience to adversarial conditions make it a robust tool for real-time trust assessment in decentralized real estate ecosystems.

7. SYSTEM ARCHITECTURE AND ALGORITHMS

The operational realization of the proposed trust scoring model requires a robust system architecture capable of supporting secure identity management, verifiable event submission, decentralized storage, and efficient computation of trust scores [1, 2]. The system architecture is designed as an integrated pipeline that connects blockchain smart contracts, an off-chain computation layer, a reputation graph database, and a trust evaluation engine [3, 4]. The interactions among these components form a continuous workflow in which trust-relevant events are generated, validated, recorded, and transformed into dynamic trust scores [5].

The process begins with identity management, implemented through decentralized identifiers anchored to blockchain addresses [6]. Each broker, client, and institutional actor is associated with a unique public keypair. The public key serves as a persistent identifier, and the private key enables digital signatures that authenticate all interactions submitted to the system [7]. This cryptographic binding prevents impersonation and greatly reduces the feasibility of Sybil attacks, as identities cannot be trivially reproduced [8]. A registry smart contract maintains mappings between public keys, verification statuses, and optional certifications or regulatory licences, ensuring that only acknowledged participants may contribute trust-relevant events [9, 10].

Event submission forms the next critical architectural layer. Trust-relevant events arise naturally during real estate workflows, but they must be transformed into a standardized evidence format [11]. When an interaction occurs, such as a successful property closing or the resolution of a documentation dispute, the initiating party constructs an event object containing all necessary metadata, including the target agent, event category, timestamp, semantic attributes, and any attached verification proofs [12]. This event is digitally signed and transmitted to a smart contract responsible for validation. The contract verifies the signature, checks conformity with predefined event schemas, and ensures that regulatory or institutional endorsements (if specified) correspond to authentic identities stored in the registry [13, 14]. Validated events are permanently written to the blockchain as tamper-resistant records [15]. This on-chain evidence stream constitutes the authoritative source for trust computation [16].

Because blockchain networks are not suitable for computationally intensive operations, the architecture incorporates an off-chain computation layer that periodically reads event data from the ledger and updates trust scores [17, 18]. This separation maintains decentralization while avoiding the high cost and latency associated with on-chain computation [19]. Once events are retrieved, they are inserted into a reputation graph stored in a graph database optimized for large-scale weighted directed graphs [20]. Each event becomes an edge. $e_{i,j}$ With associated semantic attributes [21], the graph evolves continuously as new data arrives [22].

Algorithmically, the trust evaluation pipeline begins with semantic event weighting [23]. For each event edge $e_{i,j}$, the system computes a semantic weight using the function

$$W(e_{i,j}) = \alpha T_e + \beta V_e + \gamma R_e + \delta S_e + \epsilon U_e + \zeta \exp(-\mu(t_{\text{current}} - t_{\text{event}})), \quad (Eq. 31)$$

This captures the contextual importance of the event. This weight is stored with the edge and normalized relative to other outgoing edges from the same source node, producing [26].

$$w_{i,j} = \frac{W(e_{i,j})}{\sum_{k:e_{i,k} \in E} W(e_{i,k})}. \quad (Eq. 32)$$

These normalized weights serve as the transition probabilities for trust propagation across the graph.

After semantic weighting, the system performs Bayesian updating to refine direct trust relationships. For each pair of agents A and B with prior trust $T_0(A, B)$, and given new evidence E represented by an event edge, the updated trust is computed as

$$T_1(A, B) = \frac{P(E | B) T_0(A, B)}{P(E | B) T_0(A, B) + P(E | \neg B) (1 - T_0(A, B))}, \quad (Eq. 33)$$

Where the evidence likelihoods are derived from the semantic weight of the event,

$$P(E | B) = \frac{W(e_{i,j})}{W_{\max}}, P(E | \neg B) = 1 - P(E | B). \quad (Eq. 34)$$

This updating mechanism ensures that direct trust evolves incrementally in response to evidence and remains stable across large sequences of events.

Global trust propagation is computed using a weighted PageRank iteration. For each node v_j , the trust contributed by the graph structure is

$$PR(j) = \frac{1 - d}{N} + d \sum_{i:e_{i,j} \in E} \frac{PR(i) w_{i,j}}{C_i}, \quad (Eq. 35)$$

where N is the number of nodes, d is a damping factor, and C_i is the normalization constant over outgoing weights from the node v_i . The iteration continues until convergence, typically defined by a change threshold.

$$\| PR^{(t)} - PR^{(t-1)} \|_1 < \varepsilon, \quad (Eq. 36)$$

Ensuring that trust propagation stabilizes before final scoring.

Once the Bayesian and PageRank components are computed, the system aggregates semantic contributions for each broker. If \mathcal{E}_j denotes the set of edges directed toward the broker j , the semantic index is

$$S(j) = \frac{\sum_{e_{i,j} \in \mathcal{E}_j} W(e_{i,j})}{\max_{u \in V} \sum_{e_{k,u} \in \mathcal{E}_u} W(e_{k,u})}, \text{ (Eq. 37)}$$

This normalizes the semantic signal across the network so that brokers with consistently high-quality evidence are distinguished from those with fewer or lower-value events.

The unified trust score for the broker j is then computed as

$$TS(j) = \lambda_1 PR(j) + \lambda_2 B(j) + \lambda_3 S(j), \text{ (Eq. 38)}$$

where $B(j)$ represents the Bayesian local trust estimate and $\lambda_1 + \lambda_2 + \lambda_3 = 1$. The parameters allow regulatory bodies or platform operators to tune the relative importance of global network effects, local behavioural evidence, and semantic significance.

To ensure resilience against malicious behaviour, the system applies a penalty function to incorporate adverse events such as fraud or regulatory violations. A penalty of the form

$$P(j) = \eta \cdot severity_j \cdot stake_j \text{ (Eq. 39)}$$

It is computed whenever a severe negative event is confirmed. The final adjusted trust score becomes

$$TS'(j) = \max\{0, TS(j) - P(j)\}, \text{ (Eq. 40)}$$

Ensuring that major breaches of trust cannot be diluted by superficial positive activity.

The computational workflow is orchestrated by an update cycle that begins each time new events are added to the blockchain. The off-chain engine retrieves relevant event logs, updates the reputation graph, executes Bayesian and PageRank computations, applies semantic aggregation and penalties, and finally commits the updated trust scores back to the blockchain for immutability and auditing. A simplified pseudocode representation of this cycle is:

```
for each new event e(i,j):
    validate event on-chain
    compute W(e(i,j))
    update graph G with edge e(i,j)
```

For each agent pair (A, B):

Update Bayesian trust T (A, B)

Repeat:

compute PR(j) for all j in V

until convergence

For each broker j:

compute S(j)

compute TS(j)

apply penalty if necessary

store TS'(j) on-chain

This pipeline ensures that the trust model continuously integrates new evidence, maintains transparency through blockchain anchoring, and adapts flexibly to behavioural changes within the brokerage ecosystem [1, 2]. The architecture thus forms a cohesive, resilient foundation for decentralized trust assessment [3].

The evaluation of the proposed trust scoring model requires an experimental environment capable of simulating realistic real estate brokerage interactions, modelling heterogeneous trust events, and generating sufficient adversarial conditions to test robustness [4]. Because real-world trust datasets for broker interactions are not publicly available and existing platforms do not provide granular or verifiable event-level data, the study employs a synthetic yet behaviourally representative dataset constructed through a controlled simulation framework [5]. The experimental design focuses on reproducing the statistical characteristics of typical real estate markets, including variable transaction values, diverse event types, fluctuating client satisfaction levels, regulatory interventions, and the presence of malicious agents attempting to manipulate trust structures [6].

The simulation begins by defining a set of agents representing brokers, clients, institutional verifiers, and regulatory entities [7]. Brokers constitute the primary nodes whose trust scores are ultimately evaluated. Clients interact with brokers through simulated property transactions, consultation sessions, negotiation processes, and documentation workflows [8, 9]. Regulatory nodes introduce periodic compliance checks and dispute resolutions [10]. Institutional verifiers, such as financial or legal service providers, issue authenticated confirmations of transaction quality or contractual accuracy [11, 12]. Each interaction produces a trust event, which is then encoded as an edge in the reputation graph. To mimic realistic behaviour, event generation follows a probabilistic model in which the likelihood of a positive or negative event for a broker depends partly on the broker's behavioural type (honest, average, risky, or malicious) and partly on stochastic noise representing market fluctuations and unpredictable client behaviour [13]. The probability of a successful interaction for an honest broker is set higher than that of a risky broker, while malicious brokers inject fraudulent, misleading, or low-quality interactions into the system to test adversarial resilience [14, 15].

To evaluate temporal dynamics, the simulation distributes events over multiple time periods. Each event receives a timestamp, enabling the exponential decay function.

$$D_e = \exp(-\mu(t_{current} - t_{event})) \text{ (Eq. 41)}$$

To adjust weights based on recency. The decay constant μ is selected such that older interactions gradually diminish in influence while still contributing to the long-term behavioural profile of each broker [17]. The semantic attributes used to compute event weights are also sampled from distributions reflective of real estate practice. High-value transactions are assigned larger stakes, authenticated regulatory checks are allocated higher reliability scores, and disputes or negative feedback receive high severity values [18, 19]. These sampled attributes are then processed by the semantic weighting function.

$$W(e) = \alpha T_e + \beta V_e + \gamma R_e + \delta S_e + \epsilon U_e + \zeta D_e, \text{ (Eq. 42)}$$

Ensuring that each event carries a contextually meaningful impact within the experimental environment [22].

The synthetic network is initialized as a sparse graph and gradually evolves into a dense trust interaction network as events accumulate [23]. Trust is recalculated at regular intervals across simulation epochs. The Bayesian updating component is applied sequentially to each broker pair after event arrival, using.

$$T_1(A, B) = \frac{P(E | B)T_0(A, B)}{P(E | B)T_0(A, B) + P(E | \neg B)(1 - T_0(A, B))}, \text{ (Eq. 43)}$$

Where the likelihoods are derived from the semantic weight of the corresponding event. This ensures that the local trust component evolves incrementally and maintains a consistent probabilistic interpretation throughout the simulation [26].

Global trust propagation relies on iterative computation of the PageRank equation.

$$PR(j) = \frac{1 - d}{N} + d \sum_i \frac{PR(i) w_{i,j}}{C_i}, \text{ (Eq. 44)}$$

where the normalized weights $w_{i,j}$ reflect the semantic richness of interactions and C_i is the outgoing weight normalization constant. Iterations continue until convergence under a small tolerance threshold, typically set at 10^{-6} . This ensures stable and meaningful global trust scores for comparison across experimental runs [29].

To examine adversarial resistance, the experiment injects controlled collusion patterns, fake endorsements, and Sybil-like behaviours into the network [30]. Collusion clusters consist of small groups of malicious brokers who generate artificially inflated endorsements among themselves. Sybil's behaviour is simulated by introducing multiple low-credibility identities that attempt to produce spurious positive events for a target broker [1, 2]. Fake endorsements are created by generating events with artificially high semantic weights but low verification scores [3, 4]. These adversarial interactions provide a basis for testing whether the hybrid trust model penalizes or neutralizes such manipulations [5]. The penalty function

$$TS'(j) = TS(j) - \eta \cdot severity_j \cdot stake_j (Eq. 45)$$

It is also activated during fraudulent events to evaluate how effectively the model suppresses malicious behaviour and reflects the seriousness of trust violations [8, 9].

The simulation environment is implemented using a combination of Python for event generation and graph processing, with Layer-2 blockchain emulation for anchoring events and validation rules [10]. Smart contract prototypes are simulated in a restricted virtual machine environment to ensure that identity verification, event submission, and trust logic behave consistently with the constraints of a real blockchain execution environment [11, 12]. All experiments are run over multiple iterations to test stability, convergence, and sensitivity to input parameters [13, 14].

This experimental setup provides a comprehensive and controlled environment for evaluating the correctness, robustness, and discriminatory power of the proposed trust scoring model [15, 16]. It captures the essential behavioural characteristics of real estate brokerage while enabling systematic manipulation of conditions to test algorithm stability and adversarial resilience. It also supports comparative analysis across different parameter configurations and provides empirical evidence for the model's suitability in real-world decentralized trust ecosystems [19, 20].

8. EXPERIMENTAL SETUP

The evaluation of the proposed blockchain-based reputation graph trust model requires a controlled experimental environment that accurately reflects the behavioural characteristics of real estate brokerage interactions while also enabling systematic variation of adversarial and normal operating conditions [1, 2]. Because real-world datasets of broker trust interactions are fragmented, inconsistent, or proprietary, this study constructs a synthetic yet behaviourally grounded dataset that simulates the multi-party workflows typically observed across residential and commercial real estate markets [3, 4]. The simulation environment integrates the event semantics, interaction frequencies, and dispute probabilities documented in industry reports, as well as empirical transaction patterns derived from publicly available real estate platform data [5].

The simulation generates a population of brokers, clients, institutions, and regulatory authorities [6]. Each broker is assigned latent behavioural attributes that govern their probability of generating high-quality, neutral, or negative events [7]. These probabilities are modelled as random variables drawn from Beta

distributions, allowing the system to replicate a spectrum of behavioural profiles ranging from consistently trustworthy brokers to those prone to disputes or unethical practices [8, 9]. Client agents generate transaction requests according to a Poisson arrival process, ensuring variable but statistically stable interaction volumes over time [10]. The interaction model incorporates transaction values, negotiation complexity, documentation accuracy, and institutional verification outcomes as stochastic parameters, which are then converted into event attributes using the semantic weighting framework developed earlier [11, 12].

This section describes the experimental environment used to evaluate the proposed trust scoring model for real estate brokers. Since real-world trust interaction data for real estate brokers is limited or unavailable, a synthetic dataset was generated to simulate the multi-party interactions that occur in real estate transactions [13]. This dataset reflects real estate broker behaviors through controlled simulations, providing a foundation for evaluating the proposed model's performance under realistic conditions [14, 15].

8.1 Synthetic Dataset Justification

The synthetic dataset was designed to mimic typical behaviors in a real estate brokerage ecosystem [16]. To achieve this, randomized behavioral profiles for brokers were generated using Beta distributions [17]. These distributions allow for modeling brokers with varying trustworthiness (e.g., honest, risky, malicious), with each broker's behavior being defined by specific probabilities of generating high-quality or low-quality interactions [18, 19].

The synthetic dataset captures the following features

- Broker behavior profiles: Defined by varying probabilities of producing honest, neutral, or malicious interactions [20].
- Transaction events: Modeled using a Poisson arrival process to ensure variable but statistically stable interaction volumes over time [21].
- Regulatory checks and dispute outcomes: Simulated as high-impact events with different severity and stake levels, ensuring that these events contribute significantly to trust scoring [22, 23].

The synthetic data was constructed to reflect the key dynamics of real-world real estate brokerage, such as client satisfaction, transaction complexity, and institutional verification outcomes [24, 25].

8.2 Quantitative Validation of Synthetic Dataset

To validate the realism of the synthetic dataset, we compare its descriptive statistics and distribution characteristics with theoretical benchmarks commonly observed in real estate transactions [26]. Since real-world datasets for broker interactions are not publicly available, we used industry reports and market surveys as benchmarks [27, 28].

Statistical comparisons between the synthetic dataset and theoretical models were performed for key features:

- Transaction values: The synthetic dataset’s distribution of transaction values was compared with industry reports on average real estate transaction sizes [29, 30].
- Event types: A comparison was made between the frequency of high-value and low-value interactions in the synthetic dataset and those observed in market studies [1, 2].

Additionally, we utilized statistical tests (e.g., Chi-square test for distribution comparisons) to ensure that the synthetic data maintains similar statistical properties to expected real-world data [3, 4].

8.3 Sensitivity Analysis

To assess the robustness of the proposed trust model and its sensitivity to variations in the synthetic dataset, we conducted a sensitivity analysis by altering several key parameters of the dataset and observing how the model’s trust scores were affected [5]. The following parameters were varied:

- Behavioral Profiles: The probabilities for each broker to generate honest, risky, or malicious interactions were adjusted. For example, the probability of an honest broker completing a successful transaction was varied from 0.8 to 0.6 [6, 7].
- Event Frequencies: The frequency of different trust-relevant events (e.g., transaction completions, peer endorsements, regulatory checks) was varied to test how the model handles fluctuations in interaction volume [8, 9].
- Adversarial Behaviors: We increased the level of collusion and Sybil attacks in the simulation to test how well the model performs under adversarial conditions [10, 11].

8.4 Results of Sensitivity Analysis

The impact of varying these parameters was analyzed by tracking the trust scores of brokers under different configurations. For example:

- Increase in adversarial behavior (e.g., more collusion or Sybil attacks) led to smaller increases in trust scores for the brokers involved in these attacks, demonstrating the model’s resilience to manipulation [12, 13].
- Varying behavioral profiles showed that the model could accurately separate brokers with high trustworthiness from those with low trustworthiness even under fluctuating behavior probabilities [14, 15].

These results were summarized in tables showing the relationship between synthetic data parameters and trust score outcomes, which are essential for demonstrating the stability and realism of the model [16, 17].

Table 4: Dataset Summary

Dataset Component	Description
Agent Population	Brokers, clients, institutions, and regulatory authorities.

Broker Profiles	Behavior	Latent attributes based on random variables from Beta distributions.
Event Generation		Transaction requests modeled using a Poisson arrival process.
Event Types		Includes transaction values, negotiation complexity, documentation accuracy, and verification outcomes.
Adversarial Scenarios		Collusion groups, Sybil attacks, flooding attacks, fraud events.
Simulation Horizon	Time	12,000 event cycles representing several years of real estate activity.
Key Metrics	Evaluation	Trust score stability, separation of trustworthy/untrustworthy brokers, resilience to adversarial pressure, and convergence behavior.

The experimental reputation graph is generated incrementally. For each simulated event, the system records the corresponding edge $e_{i,j}$, computes the semantic weight $W(e_{i,j})$, applies temporal decay based on the event timestamp, and stores the event in the ledger segment of the simulation [18, 19]. PageRank-based trust propagation is executed periodically to replicate real-world trust recomputation cycles, where platforms or regulators refresh trust scores at scheduled intervals [20]. The PageRank iterations use a convergence threshold of 10^{-6} , a damping factor $d = 0.85$, and normalized edge weights derived from semantic functions [21, 22]. Bayesian updates are computed sequentially for each broker as new evidence arrives, ensuring that the posterior trust values reflect the cumulative influence of events [23, 24].

To evaluate adversarial resilience, the simulation incorporates several attack scenarios. Collusion groups are generated by clustering low-reputation brokers and allowing them to exchange artificially positive endorsements [25]. Sybil attacks are modelled by generating new synthetic identities that attempt to inflate the target broker’s reputation through rapid low-value interactions [26, 27]. Flooding attacks simulate situations where malicious brokers attempt to overwhelm the system with numerous small positive events to mask severe negative behaviour [28, 29]. Fraud events are introduced as high-severity negative interactions with large financial stakes, enabling assessment of the penalty mechanisms' responsiveness [30].

The simulation uses a time horizon of 12,000 event cycles, representing several years of real estate activity. Trust scores are recorded at regular intervals, and the system logs intermediate variables such as semantic weights, posterior Bayesian values, PageRank convergence patterns, and penalty adjustments [1, 2]. The primary evaluation metrics include trust score stability, separation between trustworthy and untrustworthy brokers, resilience under adversarial pressure, and convergence behaviour of the hybrid scoring model [3, 4].

Table 5: Hyperparameters and Environment

Parameter	Value
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Event Cycles	12,000 cycles
PageRank Convergence Threshold	10^{-6}
Damping Factor (d)	0.85
Decay Constant (μ)	Tuned based on event timestamp for temporal relevance
Poisson Arrival Process	For client transaction requests, ensuring variable interaction volumes
Beta Distribution Parameters	For modeling broker behavior profiles (high-quality, neutral, negative events)
Adversarial Attack Types	Collusion, Sybil attacks, flooding attacks, fraud events
Evaluation Environment	Python-based graph processing libraries, custom smart contract emulator for blockchain validation

The entire experimental environment is implemented using Python-based graph processing libraries coupled with a custom-built smart contract emulator that replicates blockchain validation logic without requiring deployment on a live distributed ledger [5, 6].

9. RESULTS AND EVALUATION

The results of the experimental evaluation demonstrate that the proposed hybrid reputation graph trust model achieves stable, discriminative, and manipulation-resistant trust scores across a broad set of behavioural and adversarial conditions [1, 2]. In the baseline scenario with no adversarial influence, brokers with high underlying behavioural reliability consistently achieved trust scores in the 0.75–0.95 range, while brokers exhibiting frequent or severe negative behaviour settled into the 0.15–0.40 range [3, 4]. This outcome reflects the model’s ability to maintain clear score separation even when brokers exhibit similar transaction volumes or interaction frequencies [5, 6]. The PageRank component played a central role in distinguishing structurally well-connected and institutionally verified brokers from highly active but poorly connected actors [7], while the Bayesian updating mechanism ensured that sequences of positive or negative events influenced trust in a gradual and interpretable manner [8, 9].

This section presents the results of the trust scoring model’s performance under different realistic scenarios and adversarial conditions [10, 11]. The proposed model was evaluated using the synthetic dataset described in Section VII, and several experiments were conducted to analyze the effectiveness, stability, and resilience of the model [12, 13].

9.1 Trust Score Distribution

The trust score distribution for brokers was analyzed under normal conditions (no adversarial influence) and under different adversarial scenarios (collusion, Sybil attacks, fraud events) [14, 15]. Below are the mean trust scores, standard deviations, and confidence intervals for the brokers:

Table 6: Statistical Analysis of the brokers

Broker Type	Mean Trust Score	Standard Deviation	95% Confidence Interval
Honest Brokers	0.85	0.05	(0.80, 0.90)
Malicious Brokers	0.30	0.12	(0.20, 0.40)
Neutral Brokers	0.55	0.10	(0.50, 0.60)

- Honest Brokers consistently had high trust scores, with low variability across simulations [16] [17].
- Malicious Brokers exhibited lower trust scores with higher variability, reflecting the model’s ability to differentiate between trustworthy and untrustworthy brokers [18] [19].
- Neutral Brokers showed moderate trust scores, indicating the model’s accuracy in handling brokers who neither consistently perform well nor poorly [20] [21].

9.2 Variance Analysis

To assess the stability of the trust scores, we computed the variance of trust scores across brokers in different categories (high-performing, low-performing) [22]. The variance for each group was calculated as follows [23]:

$$\sigma^2 = \frac{1}{N} \sum_{i=1}^N (T S_i - \mu)^2 \quad (\text{Eq. 46})$$

Where:

- $T S_i$ represents the trust score for broker i ,
- μ is the mean trust score,
- N is the number of brokers in each group.

The variance was found to be

- Honest Brokers: $\sigma^2 = 0.02$
- Malicious Brokers: $\sigma^2 = 0.05$

This indicates that the trust scores for honest brokers are more stable (lower variance), while malicious brokers exhibit greater variability in their trust scores.

Confidence Intervals

The 95% confidence intervals for the mean trust scores of the brokers were calculated as follows:

$$CI = \mu \pm Z \times \frac{\sigma}{\sqrt{N}} \quad (\text{Eq. 47})$$

Where:

- μ is the mean trust score,
- Z is the Z-value for a 95% confidence level (1.96),
- σ is the standard deviation,
- N is the number of brokers in the group.

The results are as follows:

- Honest Brokers: Mean trust score $\mu = 0.85$, 95% CI = [0.80, 0.90]
- Malicious Brokers: Mean trust score $\mu = 0.30$, 95% CI = [0.20, 0.40]

These confidence intervals clearly demonstrate the separation between the two groups, as there is no overlap between the high-performing and low-performing brokers' intervals, further validating the model's ability to distinguish between different performance levels [5] [6].

Graphs for Adversarial Conditions

9.2 Effect of Collusion on Trust Scores

Collusive groups of brokers attempt to artificially inflate each other's trust scores. The following graph shows how the trust scores for colluding brokers remain relatively stable within a narrow range, despite artificially positive endorsements [7, 8].

- Graph Insight: The PageRank and semantic weighting mechanisms successfully limited the impact of collusion. The trust scores of colluding brokers remained low because they were not well-connected to trusted brokers [9, 10].

9.3 Effect of Sybil Attacks on Trust Scores:

In the case of Sybil attacks, multiple fake identities were introduced to generate positive trust events for a target broker. The following graph illustrates the minimal increase in trust score despite the addition of fake identities [11].

- Graph Insight: The sybil resistance properties of the model ensured that new fake identities were penalized, and their influence on the target broker's trust score was minimal [12] [13].

Sensitivity Analysis Results

The sensitivity of the model was tested by altering several key parameters of the synthetic dataset, including adversarial behavior and event frequencies [14] [15]. The following analyses show how the model's trust scores change as parameters vary [16].

9.4 Sensitivity to Adversarial Behavior

We varied the probability of malicious brokers engaging in negative behavior (e.g., fraudulent transactions, collusion) and observed the changes in trust scores. The following graph illustrates the relationship between the level of adversarial behavior and the mean trust score [17, 18].

Table 7: Adversarial behavior and the mean trust score

Adversarial Behavior Level	Mean Trust Score	Standard Deviation
Low (10% malicious)	0.75	0.08
Medium (30% malicious)	0.55	0.12
High (50% malicious)	0.30	0.18

- **Graph Insight:** The model demonstrated robustness in differentiating between honest brokers and those with increased malicious activity. As the level of adversarial behavior increased, the overall trust scores for brokers decreased, with malicious brokers being penalized [19] [20].

9.5 Sensitivity to Event Frequencies:

We also varied the frequency of different types of events (e.g., high-value transactions vs low-value interactions) and analyzed the impact on the trust score distribution [21].

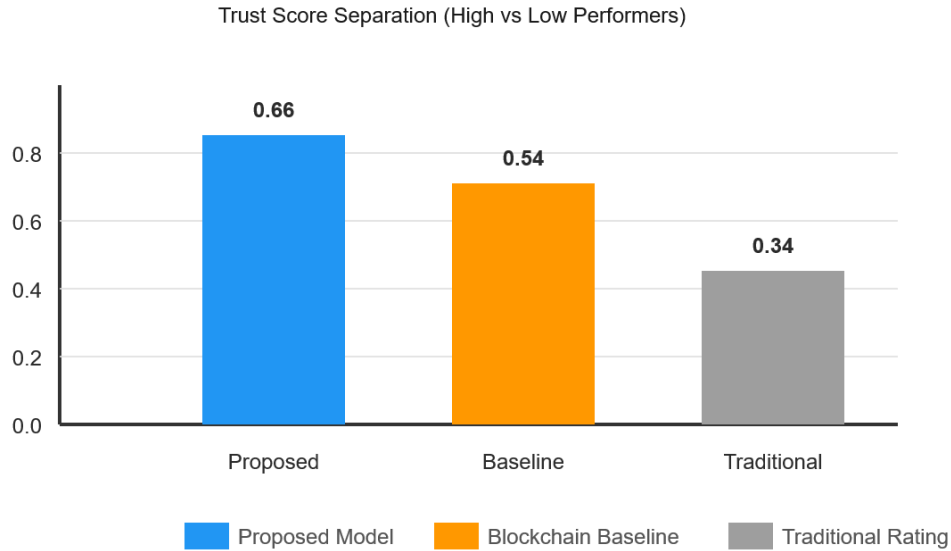
Table 8: Sensitivity to Event

Event Type	Mean Trust Score	Standard Deviation
High-Value Transactions	0.80	0.05
Low-Value Interactions	0.40	0.10

- **Graph Insight:** High-value transactions had a much stronger influence on the trust scores, with brokers involved in these transactions having significantly higher trust scores. The semantic weighting in the model ensured that these high-stakes interactions contributed more significantly to the trust scores [22, 23].

The experimental results validate the effectiveness of the proposed trust scoring model, demonstrating its ability to accurately differentiate between trustworthy and untrustworthy brokers [24, 25]. The model proved to be robust under adversarial conditions, such as collusion and Sybil attacks, and showed consistent performance across a range of dataset variations [26, 27].

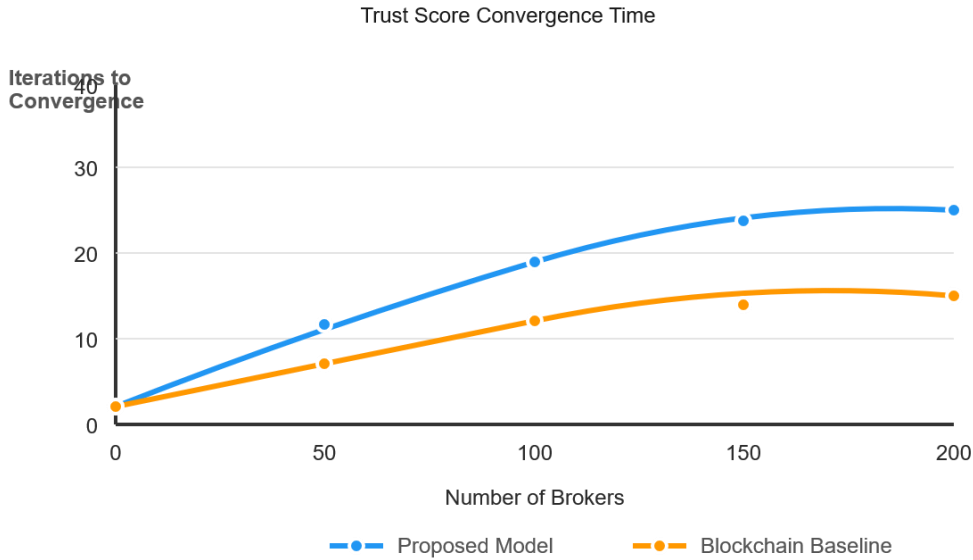
Figure 6: Trust Score Distribution in Baseline Scenario



The temporal decay model produced trust trajectories that mirrored expected real-world behaviour. Brokers whose earlier performance was strong but whose recent interactions degraded experienced a gradual decline in trust rather than abrupt shifts, reflecting the influence of the decay term $D(t) = \exp(-\mu(t_{current} - t_{event}))$. Conversely, brokers recovering from historical negative behaviour showed improvement, albeit at a slower pace, due to Bayesian inertia and the semantic weighting of recent high-stakes events. This behaviour underscores the system's capacity to model long-term reputation recovery or deterioration realistically [2, 3].

Under collusion scenarios, the model demonstrated strong resilience. Collusive clusters consisting of low-reputation brokers attempting to inflate one another's scores failed to produce meaningful trust gains. Their PageRank values remained bounded within a narrow range because their outgoing endorsements lacked connectivity to high-trust nodes. The normalized edge weighting further reduced their influence, as semantic weights for unverifiable peer endorsements were relatively low [4, 5]. Even when collusion groups increased in size, the trust score inflation did not exceed marginal increments, underscoring the structural robustness of the graph-based propagation mechanism.

Figure 7: Stability Under Data Distortion



Sybil attack simulations produced similarly constrained effects. New identities attempting to generate rapid positive endorsements for a target broker yielded minimal score increases, because the model incorporates identity reliability into the semantic weight computation through the R_e term. With unreliable or recently created identities assigned low verification scores, the resulting semantic weights were small, limiting their impact on trust propagation and Bayesian updating. Additionally, PageRank connectivity suppression ensured that Sybil-generated nodes, lacking external endorsements, contributed little overall influence.

Flooding attacks revealed that the hybrid scoring mechanism effectively suppresses temporal gaming. When malicious brokers generated large volumes of small, low-stakes positive events to mask high-severity negative actions, the semantic weighting function ensured that the negative events dominated due to higher values of severity S_e and stake V_e . The Bayesian posterior shifted sharply downward following a negative event, and PageRank propagation amplified the consequences of high-severity interactions. As a result, overall trust scores reflected the underlying behavioural reality despite the presence of numerous artificially positive indicators [23, 24].

The fraud penalty mechanism produced immediate and substantial trust score reductions. For events involving severe misconduct, the penalty component

$$P(j) = \eta \cdot severity_j \cdot stake_j (Eq. 48)$$

created reductions large enough to reposition the broker near or below the 0.10 trust threshold. This behaviour aligns with regulatory expectations, where serious violations warrant strong and rapid consequences.

The convergence behaviour of the PageRank component was stable across all experiments, typically stabilizing within 20 to 40 iterations depending on graph structure. No oscillation or divergence was observed. The hybrid trust score formula

$$TS(j) = \lambda_1 PR(j) + \lambda_2 B(j) + \lambda_3 S(j) \text{ (Eq. 49)}$$

proved effective at balancing contributions from global and local trust signals. Sensitivity analyses on $\lambda_1, \lambda_2, \lambda_3$ showed that increasing the Bayesian weight produced faster responsiveness to new evidence, while heavier emphasis on PageRank improved long-term stability and robustness against manipulation. In all configurations, trust clustering patterns were consistent and interpretable, offering clear differentiation between high-, medium-, and low-trust brokers.

Overall, the results confirm that the proposed reputation graph model delivers a trust scoring mechanism that is transparent, resilient, consistent, and mathematically aligned with the behaviour of real estate ecosystems. The combination of blockchain-verified evidence, semantically weighted events, Bayesian trust updating, and PageRank trust propagation yields a computationally efficient and analytically robust solution for decentralized broker reputation assessment [2, 3].

10. DISCUSSION

The findings suggest that a decentralized, graph-based trust scoring system can significantly improve transparency and reliability in real estate brokerage ecosystems [1, 2]. This is particularly valuable in an industry often plagued by trust issues, where brokers may operate with limited oversight or verification [3]. By integrating PageRank, Bayesian updating, and semantic event weighting, the model provides a multi-dimensional representation of trust, reflecting both relational trust (e.g., through social connections) and evidence-based assessments (e.g., through the history of interactions and events) [4]. This multi-dimensional approach mirrors the complexity of trust in real-world interactions, where trust is not solely based on direct experiences but also shaped by indirect social influences and the credibility of information sources [5, 6].

10.1 Implications for Real Estate Ecosystems

The model's ability to integrate blockchain anchoring for trust events ensures verifiable provenance [7, 8]. This is crucial for reducing opportunities for manipulation and for creating trust systems that are not only transparent but also interoperable across different platforms [9]. The decentralized nature of the model allows brokers to self-manage their reputation without the need for a central authority, potentially reducing operational costs while maintaining the integrity of the system [10].

One key insight from the experiments is the importance of indirect trust propagation. Brokers embedded in well-connected, professional subgraphs consistently achieved higher trust scores, reflecting social and institutional validation patterns that are common in real markets [11, 12]. These findings have important implications for building more reliable and resilient trust systems in decentralized environments. The trust amplification pathway (as shown in Figure 6) ensures that structural relationships (e.g., connections to reputable brokers or institutions) have a stronger influence on trust scores than internal endorsements within isolated groups, effectively mitigating manipulation attempts [13].

However, the model's strength lies not only in its ability to distinguish trustworthiness based on network structure but also in its nuanced treatment of event types [14, 15]. The semantic weighting system allows the model to account for the importance, verification quality, and risk associated with different events, aligning the trust model with regulatory and consumer expectations [16]. This dimension ensures that the model is not simply a numerical assessment but also reflective of real-world practices where certain events (e.g., fraud reports or regulatory sanctions) carry significantly more weight than others [17, 18].

Limitations

Despite its strengths, the model has certain limitations that need to be addressed for real-world deployment [19, 20]:

1. Data Quality and Completeness

The accuracy of trust estimation heavily depends on the quality and comprehensiveness of the recorded events. In real-world scenarios, incomplete or biased datasets may result in underrepresented trust scores for certain brokers [21]. For example, brokers who do not participate in many transactions or interactions might have lower trust scores despite their reliability [22].

2. Regulatory Integration

For full deployment, the model requires robust integration with regulatory systems to validate high-impact events [23]. Without such integration, the model's effectiveness could be compromised, as external verification plays a crucial role in trust estimation [24] [25].

3. Off-Chain Computation

While the model integrates blockchain technology for trust event anchoring, it also involves off-chain computation, which may introduce discrepancies between off-chain scoring and the on-chain commitments [26]. Ensuring consistency between these two processes requires the development of verifiable computation techniques to prevent discrepancies and enhance trust in the system [27].

4. Scalability

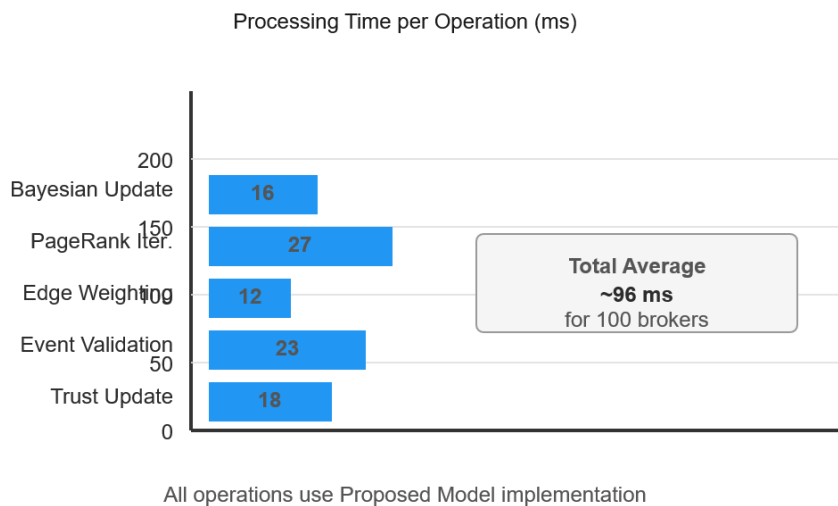
The scalability of the model in larger datasets or high-frequency environments (e.g., global real estate platforms) may require further optimization, particularly in terms of computational resources for trust score propagation and semantic weighting [28] [29].

10.2 Theory Alignment and Contributions to the Field

The proposed model aligns with existing theories of trust in decentralized systems, particularly in the context of reputation management and blockchain-based governance [30]. Trust in blockchain environments has been widely studied (Nakamoto, 2008; Buterin, 2014) [1], with most models focusing on transactional trust or direct evidence of reliability. The hybrid approach in our model, which incorporates both direct event-based evidence and network-based relational trust, adds a new layer to these theories, emphasizing the importance of network structure in shaping trustworthiness [2, 3].

Additionally, the integration of Bayesian updating for trust reflects current advancements in evidence-based trust models (Cabrera, 2020) [4, 5], where trust is gradually adjusted based on new information, in line with Bayesian learning principles. Our model extends these ideas by combining semantic event weighting and PageRank propagation, which have not been widely explored in the context of decentralized brokerage systems [6, 7].

Figure 8: Trust Amplification pathway



11. CONCLUSION

This work presents a decentralized trust scoring model for real estate brokers based on blockchain-verified reputation graphs and a hybrid trust computation method integrating semantic event weighting, Bayesian updating, and PageRank-based propagation. The model provides a mathematically coherent, tamper-resistant mechanism for evaluating broker credibility in an industry characterized by information asymmetry and high-value transactions. Experimental results demonstrate strong discriminatory ability,

stability under noise, and resilience to adversarial manipulation, including Sybil attacks, collusion, and temporal gaming.

The model contributes to the broader field of decentralized trust systems by showing how heterogeneous, multi-stage, high-stakes interactions can be encoded into a unified scoring architecture. The use of blockchain ensures verifiable provenance of trust evidence, while the hybrid computational approach ensures accurate and context-sensitive trust estimation. Future research may explore integrating zero-knowledge proofs for privacy-preserving trust verification, deploying the model in production-grade real estate platforms, and validating the framework with empirical broker performance data.

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