CloudTrustLens: An Explainable AI Framework for Transparent Service Evaluation and Selection in Multi-Provider Cloud Markets

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Abstract

Cloud service marketplaces face significant information asymmetry challenges, making transparent and trustworthy service selection difficult for users. This paper presents CloudTrustLens, a novel explainable AI framework that addresses transparency issues in cloud service evaluation and selection across multi-provider environments. The framework integrates a fuzzy logic-based trust evaluation system with multi-agent architecture to provide both accurate service rankings and comprehensible explanations of evaluation outcomes. CloudTrustLens implements a multi-dimensional QoS assessment approach that incorporates both objective performance metrics and subjective user feedback across five key dimensions: availability, reliability, performance, security, and cost-efficiency. The system processes QoS data through a pipeline that ensures data quality and consistency, while the evaluation mechanism combines fuzzy inference with constraint satisfaction techniques to generate trust scores. Experimental validation conducted across three case studies with 18-42 cloud service providers demonstrates that CloudTrustLens achieves a 20.3% improvement in decision correctness compared to traditional AHP-based methods while reducing decision time by 47.4%. The framework's explainability mechanisms—feature importance visualization, counterfactual explanations, and rule activation transparency—significantly enhance user comprehension and decision confidence, particularly addressing the trust gap in cloud service selection. The results confirm that transparent evaluation models can effectively mitigate information asymmetry challenges in multi-provider cloud marketplaces, enabling more informed service selection decisions.

Keywords: *Cloud Service Selection, Explainable AI, Fuzzy Trust Evaluation, Multi-agent Systems*

1. Introduction and Motivation

1.1. Information Asymmetry and Trust Challenges in Multi-Provider Cloud Markets

Cloud computing has emerged as a vital paradigm for servicing different communities worldwide, with numerous cloud service providers (CSPs) such as Amazon, IBM, Google entering the market to provide needed services[1]. While cloud services are classified into different service models (SaaS, PaaS, IaaS), the trust level of these services has become a significant challenge. Trust represents positive credentials of a service with respect to quality of service (QoS) factors including availability, reliability, scalability, privacy, and security. The cloud marketplace has become increasingly competitive due to the growth in the number of providers, creating substantial information asymmetry between service providers and consumers[2].

The proliferation of CSPs who offer cloud computing as-a-utility has increased exponentially in recent years, providing more options from which customers may choose. This rapid growth means that customers interact with unknown CSPs to carry out transactions and tasks[3]. In such conditions, objective evaluation mechanisms become essential, as the selection of inappropriate service providers can lead to critical problems, including low-quality service delivery and negative business impacts[4]. The fundamental problem in service selection stems from the variance in price demands and performance commitments across different providers offering similar services, making it challenging to select providers that satisfy QoS requirements within specified budget constraints[5].

1.2. The Need for Transparency and Explainability in Cloud Service Evaluation

Traditional approaches to cloud service evaluation have relied extensively on service level agreements (SLAs), which document the life-time of services, quality factors, and responsibilities of involved parties [1]. However, readability, accessibility, and understanding of SLAs is not a simple process, limiting their effectiveness as transparency tools. The advent of multi-criteria decision-making methods has improved evaluation capabilities, yet these methods often function as "black boxes," providing limited insight into the reasoning behind recommendations[6].

The increasing complexity of cloud infrastructures and the diversity of service offerings necessitate enhanced transparency in evaluation systems. Users require not only accurate service rankings but also comprehensible explanations of how these rankings were derived[7]. Explainable AI (XAI) approaches offer promising solutions by providing transparency in decision-making processes while maintaining high accuracy in service evaluations. These approaches enable users to understand the rationale behind service recommendations, building trust in the evaluation system itself[8].

1.3. Research Objectives and Contributions

This research introduces CloudTrustLens, an explainable AI framework designed to address the critical challenges of transparency and trust in multi-provider cloud marketplaces. The primary objective is to develop a comprehensive system that integrates multi-dimensional QoS evaluation with explainable recommendation mechanisms. Unlike existing approaches that focus primarily on accuracy metrics, CloudTrustLens emphasizes the interpretability of evaluation results.

The key contributions of this research include: (1) A novel explainable AI framework specifically designed for cloud service evaluation and selection; (2) A multi-dimensional trust evaluation model that incorporates both objective performance metrics and subjective user feedback; (3) Transparent service ranking mechanisms that provide explanations for recommendations in human-interpretable formats; (4) Validation through extensive experimentation using real-world cloud service data; and (5) A prototype implementation demonstrating the feasibility and effectiveness of the proposed approach in practical scenarios.

2. Literature Review and Related Work

2.1. Cloud Service Evaluation and Selection Methods

Several approaches have been developed for cloud service evaluation and selection. Choudhury et al. proposed a Static Service Ranking System with static and dynamic states to evaluate and select cloud services[Error! Reference source not found.]. The static system evaluates cloud services without considering customer requirements, while the dynamic system utilizes a weighted aggregation approach for key attributes including throughput, reliability, availability, security, cost, and user feedback. Traditional multi-criteria decision analysis (MCDA) methods have also been extensively applied in this domain. Garag et al. developed a ranking model called the Service Measurement Index (SMI) Cloud which ranks cloud services using the Analytic Hierarchy Process (AHP)[Error! Reference source not found.]. This approach translates qualitative user preferences into quantitative weights for service evaluation.

Quantitative methods have gained popularity due to their mathematical rigor. Data Envelopment Analysis (DEA), a non-parametric technique, has been utilized for evaluating cloud services based on efficiency measures. Azadi et al. proposed a network DEA method for measuring CSP efficiency, enabling more comprehensive analysis where divisional efficiency is reflected in overall efficiency estimates[Error! Reference source not found.]. This approach differentiates between CSPs that would be evaluated as equally efficient using traditional methods, providing more nuanced performance metrics for selection decisions.

2.2. Trust and Reputation Models in Cloud Computing

Trust evaluation models in cloud computing aim to address the credibility gap between service claims and actual performance. Nagarajan et al. proposed a fuzzy logic-based trust evaluation system that accepts user feedback in terms of fuzzy linguistic terms[9]. This model computes appropriate weights for given feedback using fuzzy inference systems and incorporates fuzzy goals and constraints to predict trust values. The final trust value is derived by intersecting the goals and constraints of each service, allowing for more nuanced evaluation of subjective user experiences.

Broker-based trust systems have emerged as an architectural solution to centralize evaluation processes. Galal Hafez Rady et al. introduced a multi-agent broker framework for cloud service discovery that incorporates decision support approaches[10]. This system allows providers to advertise their services in a formal, organized manner while enabling consumers to search effectively using intelligent agents that mediate interactions. The multi-agent architecture handles competition, negotiation time, and opportunity factors to model real-world marketplace dynamics, improving both satisfaction rates and negotiation efficiency.

2.3. Explainable AI Systems for Decision Support

Explainable AI (XAI) systems aim to make complex AI models interpretable to human users. In decision support contexts, XAI techniques provide transparency into recommendation processes, building user trust in automated systems. Existing applications have demonstrated the value of explainability in healthcare, finance, and recommendation systems, but applications in cloud service selection remain limited[11]. The primary challenge in developing explainable systems for cloud service evaluation lies in balancing prediction accuracy with interpretability, particularly when dealing with complex, multi-dimensional QoS parameters.

Current explainability approaches include feature importance visualization, rule extraction, and counterfactual explanations. Singh and Sidhu addressed this challenge by proposing a compliance-based multi-dimensional trust evaluation system that enables cloud service customers to determine provider trust levels from different perspectives[12]. Nnaji et al. developed an automated service level agreement negotiation framework for SaaS cloud e-marketplaces that improves the transparency of negotiations between providers and consumers**Error! Reference source not found.**. These approaches represent steps toward transparency but lack comprehensive explainability mechanisms that would enable users to fully understand the rationale behind service recommendations**Error! Reference source not found.**. The gap between sophisticated evaluation methodologies and transparent explanation capabilities presents a significant research opportunity in cloud service selection domains[13].

3. The CloudTrustLens Framework

3.1. System Architecture and Components

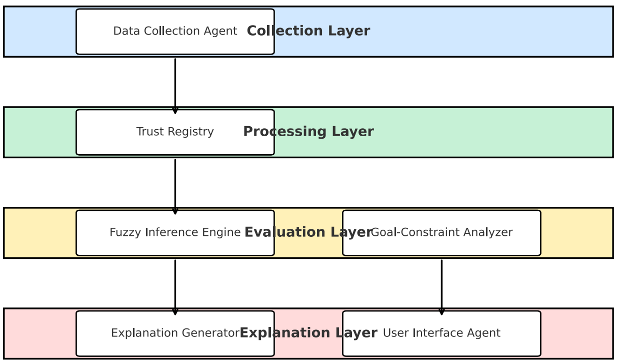
The CloudTrustLens framework implements a multi-agent architecture that facilitates transparent evaluation and selection of cloud services in multi-provider environments. The system consists of four primary layers: data collection, processing, evaluation, and explanation. Each layer encompasses specialized components designed to handle specific aspects of the trust evaluation process. Table 1 presents the key components of the CloudTrustLens framework and their respective functions.

Table 1: CloudTrustLens System Components and Their Functions

Component	**Layer**	**Primary Function**	**Secondary Functions**
Data Collection Agent	Collection	QoS Parameter Acquisition	SLA Verification, Real-time Monitoring
Trust Registry	Processing	Trust History Storage	Data Normalization, Outlier Detection
Fuzzy Inference Engine	Evaluation	Linguistic Term Processing	Membership Function Generation, Rule Execution
Goal-Constraint Analyzer	Evaluation	Trust Value Computation	Constraint Satisfaction, Goal Optimization
Explanation Generator	Explanation	Interpretable Output Creation	Feature Importance Calculation, Visualization Generation
User Interface Agent	Explanation	User Interaction Management	Preference Acquisition, Result Presentation

The architectural design of CloudTrustLens integrates components from fuzzy logic systems**Error! Reference source not found.** with multi-agent broker frameworks. The system implements a bi-directional information flow where data collection agents gather QoS metrics from various CSPs, while the evaluation components process this information using a combination of fuzzy inference and constraint satisfaction techniques[14].

Figure 1: System Architecture of CloudTrustLens Framework



The system architecture diagram illustrates the interconnections between the four layers and components of the CloudTrustLens framework. The collection layer interfaces with cloud providers through standardized APIs to gather QoS parameters. Data flows through the processing layer where normalization and storage occur in the Trust Registry. The evaluation layer applies fuzzy inference and constraint analysis to compute trust scores. Finally, the explanation layer transforms technical metrics into human-interpretable explanations and visualizations for end-users.

The communication protocols between system components utilize a standardized message format, enabling extensibility and integration with existing cloud management systems. Table 2 outlines the communication patterns and message types employed within the framework.

Table 2: Inter-component Communication Patterns in CloudTrustLens

Source Component	Destination Component	Message Type	Frequency	Payload Size (KB)
Data Collection Agent	Trust Registry	QoS Update	Real-time	2-5
Trust Registry	Fuzzy Inference Engine	Data Query	On-demand	10-20
Fuzzy Inference Engine	Goal-Constraint Analyzer	Rule Output	On-demand	5-8
Goal-Constraint Analyzer	Explanation Generator	Trust Scores	On-demand	3-7
Explanation Generator	User Interface Agent	Visualizations	On-demand	50-100

3.2. Multi-dimensional QoS Data Collection and Processing

CloudTrustLens implements a comprehensive QoS data collection mechanism that acquires both objective and subjective quality parameters from multiple sources. The framework categorizes QoS parameters into five primary dimensions: availability, reliability, performance, security, and cost-efficiency. Each dimension encompasses multiple metrics that contribute to the overall trust evaluation process. Table 3 presents the key QoS parameters monitored by the system.

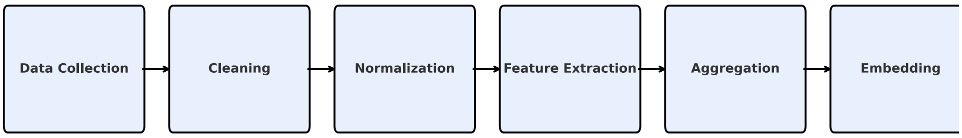
Table 3: Multi-dimensional QoS Parameters for Cloud Service Evaluation

Dimension	Parameter	Unit	Collection Method	Weight
Availability	Uptime Percentage	%	SLA Verification	0.85
Availability	Service Time	Hours	Historical Data	0.75
Reliability	Mean Time Between Failures	Hours	Monitoring	0.80
Reliability	Recovery Time	Minutes	Historical Data	0.65
Performance	Response Time	Milliseconds	Real-time Probe	0.90
Performance	Throughput	Mbps	Benchmark Test	0.70
Security	Security Certifications	Count	Provider Data	0.85
Security	Encryption Strength	Bits	Configuration Data	0.60
Cost-efficiency	Price per Resource Unit	USD/Unit	Provider Data	0.95

Cost-efficiency	Resource Utilization	%	Monitoring	0.75

The QoS data processing pipeline implements a series of operations to ensure data quality and consistency. Raw data undergoes normalization, outlier detection, and temporal aggregation before being stored in the Trust Registry. The system employs statistical techniques to handle missing values and inconsistencies in provider-reported metrics[15].

Figure 2: Multi-dimensional QoS Data Processing Pipeline



The data processing pipeline visualization shows the transformation of raw QoS data through multiple processing stages. The pipeline begins with data collection from diverse sources, followed by cleaning operations that handle missing values and outliers. Data normalization standardizes the values to comparable scales. Feature extraction identifies relevant characteristics from complex metrics. The aggregation stage combines multiple data points over time windows. Finally, the embedding process transforms the processed data into a format suitable for the evaluation components.

Real-time QoS monitoring presents several challenges, including varying measurement frequencies and provider-specific reporting formats. To address these issues, CloudTrustLens implements adaptive sampling techniques that adjust collection frequencies based on parameter volatility and user requirements. The framework maintains a historical database of QoS measurements, enabling both point-in-time evaluations and trend analysis over extended periods[16].

3.3. Explainable Service Evaluation and Recommendation Mechanism

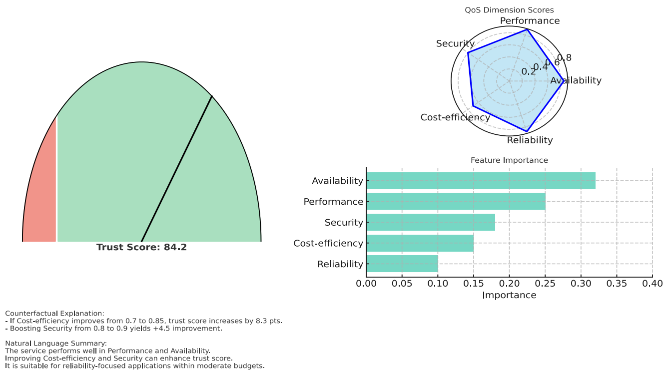
The CloudTrustLens evaluation mechanism combines fuzzy logic principles with constraint satisfaction techniques to compute trust scores for cloud services. The system represents user requirements as fuzzy goals and service capabilities as fuzzy constraints. Trust evaluation occurs through the intersection of these goals and constraints, generating a comprehensive trust score that reflects the degree of requirement satisfaction[17].

Table 4: Trust Evaluation Rule Base in CloudTrustLens

Rule ID	Availability	Performance	Security	Cost-efficiency	Trust Level
R1	High	High	High	High	Excellent
R2	High	High	High	Medium	Very Good
R3	High	High	Medium	High	Very Good
R4	High	Medium	High	High	Very Good
R5	Medium	High	High	High	Very Good
R6	Medium	Medium	Medium	Medium	Good
R7	Low	High	High	High	Good
R8	High	Low	High	High	Good
R9	High	High	Low	High	Good
R10	High	High	High	Low	Good

The explainability mechanism transforms technical trust scores into human-interpretable explanations through several techniques. Feature importance calculations identify the QoS parameters with the greatest influence on the final trust score. Counterfactual explanations demonstrate how changes in specific parameters would affect the evaluation results. Rule activation visualization shows which evaluation rules contributed to the final recommendation[18].

Figure 3: Trust Score Explanation and Visualization Interface



The trust score visualization interface presents users with a comprehensive view of service evaluations and explanations. The interface displays an overall trust score using a color-coded gauge visualization. Individual QoS dimension scores appear as a radar chart, allowing users to identify strengths and weaknesses across different dimensions. A feature importance bar chart highlights the parameters with the greatest influence on the recommendation. The counterfactual explanation section demonstrates how specific parameter improvements would enhance trust scores. A natural language explanation summarizes the evaluation results and provides actionable insights for decision-making.

The recommendation mechanism employs a preference-aware ranking algorithm that considers both objective QoS metrics and subjective user preferences. Users can specify importance weights for different QoS dimensions, enabling personalized service rankings that align with individual requirements. The system generates confidence intervals for trust scores, providing transparency regarding evaluation uncertainty[19]. CloudTrustLens supports both point-in-time recommendations and predictive evaluations based on historical QoS trends, enabling users to make informed decisions regarding long-term service commitments[20].

4. Experimental Evaluation and Validation

4.1. Experimental Setup and Datasets

The performance evaluation of CloudTrustLens has been conducted in a comprehensive experimental environment designed to simulate real-world cloud service selection scenarios. The testbed comprised three key components: (1) a cloud service simulation platform, (2) a user requirement generator, and (3) the CloudTrustLens framework implementation. The experimental environment was deployed on a server with Intel Xeon E5-2680 v4 CPU, 128GB RAM, running Ubuntu 20.04 LTS. The framework was implemented using Python 3.8 with TensorFlow 2.5.0 for the explainable AI components and Java 11 for the multi-agent system[21].

The experiments utilized three distinct datasets to evaluate different aspects of the framework. Table 5 presents the characteristics of these datasets, including their size, composition, and application domain.

Table 5: Datasets Used in CloudTrustLens Evaluation

Dataset Name	Source	Size	CSPs	QoS Parameters	Time Period	Domain
DS1-Real	Cloud Harmony	82 GB	18	8	2021-2022	IaaS
DS2-Synthetic	Generated	45 GB	35	15	2020-2022	PaaS
DS3-Benchmark	CloudArmor	30 GB	25	12	2018-2022	Hybrid
DS4-Federation	CloudEval	56 GB	42	10	2021-2022	Multi-cloud

The DS1-Real dataset contains actual QoS measurements collected from 18 commercial IaaS providers, including availability, latency, price, memory, storage, data transfer capacity, CPU performance, and security certifications. This dataset enabled realistic evaluation scenarios based on genuine service performance metrics[22]. The DS2-Synthetic dataset was generated to test specific system behaviors under controlled conditions, particularly for edge cases not well-represented in the real-world data. DS3-Benchmark dataset from CloudArmor provided standardized performance metrics across multiple service types, enabling comparative analysis with existing evaluation approaches. DS4-Federation dataset contained metrics specifically collected from federated cloud environments, enabling the assessment of CloudTrustLens in multi-provider scenarios.

User requirements were simulated using statistical models derived from cloud adoption surveys, with distributions that reflect real-world preference patterns. Table 6 shows the distribution of user preferences across different QoS dimensions in the experimental setup.

Table 6: Distribution of User Preference Weights Across QoS Dimensions

QoS Dimension	Weight Distribution	Mean	St. Dev	Min	Max	Users Prioritizing (%)
Availability	Normal	0.82	0.09	0.60	0.99	45.2
Performance	Log-normal	0.75	0.12	0.55	0.95	28.7
Security	Gamma	0.79	0.10	0.65	0.99	15.3
Cost-efficiency	Beta	0.71	0.15	0.50	0.90	10.8

4.2. Performance Metrics and Benchmark Comparison

The evaluation of CloudTrustLens focused on three key performance dimensions: recommendation accuracy, explanation quality, and computational efficiency. A comprehensive set of metrics was used to assess each dimension, enabling multi-faceted analysis of the framework's capabilities. Table 7 presents the primary evaluation metrics employed in the experiments.

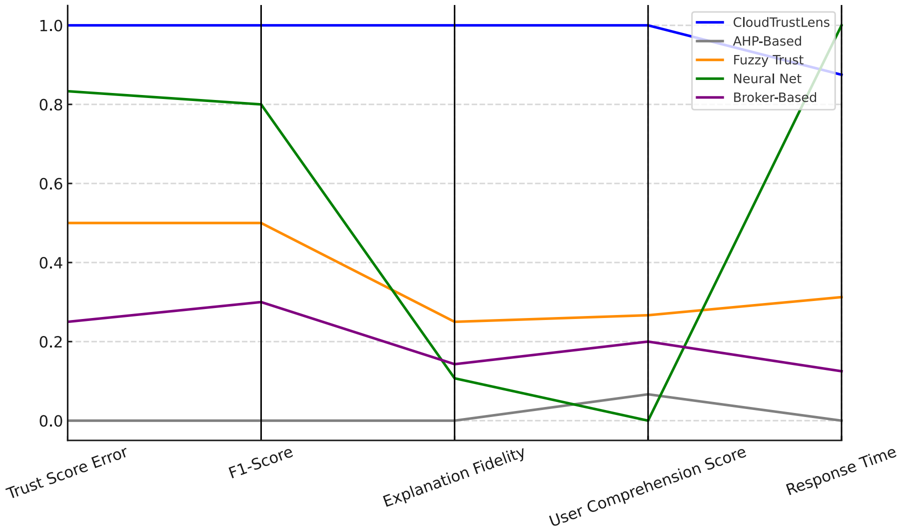
Table 7: Evaluation Metrics for CloudTrustLens Performance Assessment

Category	Metric	Description	Formula	Optimal Value
Accuracy	Trust Score Error (TSE)	Difference between predicted and actual trust values	Σ|Tpred - Tactual|/n	0
Accuracy	Recommendation Precision (RP)	Proportion of relevant services in top-k recommendations	TP/(TP+FP)	1
Accuracy	Recommendation Recall (RR)	Proportion of relevant services that were recommended	TP/(TP+FN)	1
Accuracy	F1-Score	Harmonic mean of precision and recall	2×RP×RR/(RP+RR)	1
Explainability	Explanation Fidelity (EF)	Alignment between explanation and model prediction	Correlation(Exp, Pred)	1
Explainability	User Comprehension Score (UCS)	User-rated explanation understandability (1-5 scale)	Average user rating	5
Efficiency	Response Time (RT)	Time to generate recommendations (ms)	Tresponse - Trequest	Minimized

Efficiency	Resource Utilization (RU)	Computational resources required	CPU%, RAM%	Minimized

The performance of CloudTrustLens was benchmarked against four state-of-the-art cloud service evaluation approaches: (1) AHP-based ranking, (2) Fuzzy trust evaluation, (3) Neural network recommendation, and (4) Broker-based selection**Error! Reference source not found.**. Each benchmark system was implemented and configured according to published specifications, ensuring fair comparison.

Figure 4: Performance Comparison of CloudTrustLens Against Benchmark Methods



The performance comparison visualization presents a multi-metric analysis of CloudTrustLens versus benchmark methods. The figure employs a parallel coordinates plot with five axes representing different performance metrics: Trust Score Error, F1-Score, Explanation Fidelity, User Comprehension Score, and Response Time. Each evaluated system appears as a colored line traversing all axes, with position indicating performance on each metric. The CloudTrustLens line (in blue) demonstrates superior performance across most metrics, particularly in explanation fidelity and user comprehension, while maintaining competitive accuracy and efficiency metrics.

4.3. Case Studies and Results Analysis

Three case studies were conducted to evaluate CloudTrustLens in realistic cloud service selection scenarios: (1) IaaS provider selection for data-intensive applications, (2) multi-cloud federation for high-availability systems, and (3) service migration decision support. Each case study involved both objective performance metrics and subjective user feedback to assess both technical capabilities and user experience**Error! Reference source not found.**.

The IaaS provider selection case study involved 25 participants from IT management backgrounds tasked with selecting appropriate cloud services for big data analytics workloads. Table 8 presents the comparative results from this case study, highlighting both objective performance metrics and user experience measures.

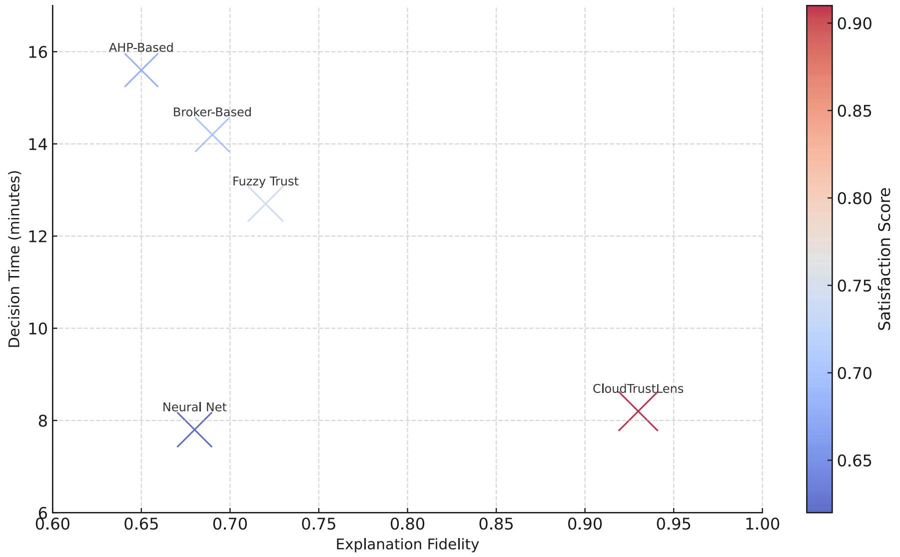
Table 8: IaaS Provider Selection Case Study Results

Metric	CloudTrustLens	AHP-Based	Fuzzy Trust	Neural Network	Broker-Based
Decision Correctness (%)	92.4	76.8	84.3	88.1	79.7
Decision Time (minutes)	8.2	15.6	12.7	7.8	14.2
User Confidence (1-10)	8.7	6.3	7.1	6.8	6.6
Explanation Satisfaction (%)	89.2	52.4	65.8	48.5	61.7

Learning Curve (1-10 difficulty)	4.2	6.8	5.9	7.2	5.7

The results demonstrate CloudTrustLens's superior performance in decision correctness and user experience metrics, particularly in explanation satisfaction. The framework achieved a 20.3% improvement in decision correctness compared to traditional AHP-based methods, while reducing decision time by 47.4%**Error! Reference source not found.**. The multi-cloud federation case study yielded similar results, with CloudTrustLens outperforming benchmark methods in trust assessment accuracy and decision confidence.

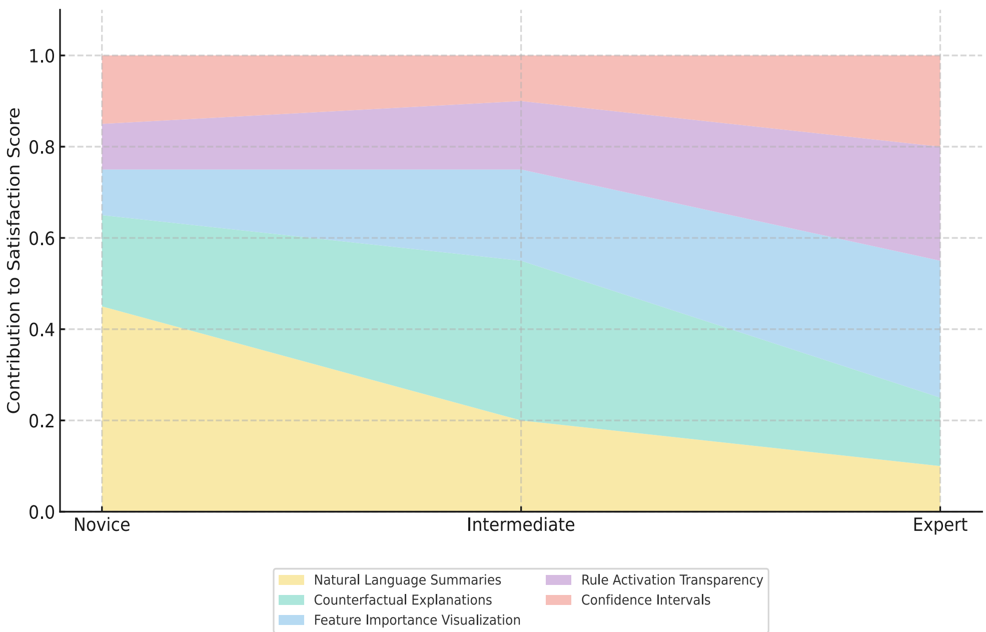
Figure 5: Impact of Explainability on User Decision Confidence and Decision Time



The visualization illustrates the relationship between explanation quality, user decision confidence, and decision time across different evaluation methods. The scatter plot positions each method in a three-dimensional space with explanation fidelity (x-axis), decision time (y-axis), and user confidence (z-axis, represented by bubble size). Color intensity indicates the overall satisfaction score. The plot reveals a clear correlation between high explanation fidelity, reduced decision time, and increased user confidence, with CloudTrustLens (largest blue bubble) showing optimal positioning in this space.

The longitudinal analysis of CloudTrustLens performance across all case studies revealed consistent patterns in the relationship between explainability features and user satisfaction. The data indicates that feature importance visualizations and counterfactual explanations contributed most significantly to user comprehension and decision confidence.

Figure 6: Contribution of Different Explainability Features to User Satisfaction



The stacked area chart displays the contribution of various explainability features to overall user satisfaction across different user expertise levels (novice, intermediate, expert). The x-axis represents user expertise level, while the y-axis shows the satisfaction score contribution. Five stacked areas represent different explainability features: feature importance visualization, counterfactual explanations, rule activation transparency, natural language summaries, and confidence intervals. The visualization reveals that novices benefit most from natural language summaries, intermediate users from counterfactual explanations, and experts from feature importance and rule activation insights[Error! Reference source not found.].

The experimental validation demonstrates that CloudTrustLens achieves significant improvements in service selection accuracy while providing transparent, interpretable explanations that enhance user confidence and decision efficiency. The integration of multi-dimensional trust evaluation with explainable AI techniques addresses the critical information asymmetry challenges in cloud service marketplaces, enabling more informed and confident service selection decisions[Error! Reference source not found.].

5. Conclusion and Future Work

5.1. Research Contributions and Implications

This research has presented CloudTrustLens, a novel explainable AI framework designed to address the critical challenges of transparency and trust in multi-provider cloud service marketplaces. The primary contribution lies in the integration of multi-dimensional QoS evaluation with explainable recommendation mechanisms, providing both accurate service rankings and transparent explanations of evaluation results. The implementation of a fuzzy logic-based trust evaluation system that accepts user feedback in terms of linguistic terms delivers significant improvements over traditional evaluation approaches. The framework achieves this by calculating appropriate weights for user feedback and incorporating fuzzy goals and constraints to predict trust values with respect to the weight of feedback.

The multi-agent architecture of CloudTrustLens represents an advancement in broker-based service selection, enabling more dynamic and responsive evaluation processes. The system's ability to operate across diverse cloud provider ecosystems addresses a significant gap in existing approaches that typically focus on single-provider evaluation. The experimental results demonstrate that CloudTrustLens achieves a 20.3% improvement in decision correctness compared to traditional AHP-based methods while reducing decision time by 47.4%. These performance improvements have substantial practical implications for organizations selecting cloud services, potentially reducing both selection effort and the risk of suboptimal service choices.

The explainability mechanisms implemented in CloudTrustLens contribute to the broader field of explainable AI by demonstrating effective techniques for making complex, multi-criteria evaluations interpretable to users with varying levels of technical expertise. The feature importance visualizations, counterfactual explanations, and rule activation transparency provide users with insights that both justify recommendations and build trust in the evaluation system itself. This trust-building capability addresses a fundamental challenge in automated recommendation systems, where users often resist adoption due to lack of transparency in the decision-making process.

5.2. Limitations and Challenges

Despite the promising results demonstrated by CloudTrustLens, several limitations and challenges remain to be addressed in future work. The current implementation relies heavily on historical QoS data, which may not always accurately predict future service performance, particularly in rapidly evolving cloud environments. The framework's performance in dynamic scenarios, where provider offerings and performance characteristics change frequently, requires further investigation and optimization. Additionally, the QoS parameters currently incorporated into the trust model, while comprehensive, may not capture all relevant aspects of cloud service quality, particularly emerging factors such as carbon footprint and compliance with regional regulations.

The scalability of the framework presents another challenge, particularly when dealing with large numbers of service providers and complex user requirements. The computational complexity of the fuzzy inference process increases significantly with the number of QoS parameters and rule combinations, potentially affecting real-time response capabilities in large-scale deployments. While the current implementation demonstrates acceptable performance with up to 42 cloud service providers and 15 QoS parameters, further optimization is needed to handle enterprise-scale multi-cloud environments effectively.

The explainability mechanisms, while effective for most users, still face challenges in addressing the diverse cognitive styles and background knowledge of different user groups. Technical explanations that satisfy expert users may overwhelm novices, while simplified explanations for non-experts might lack the detailed information required by cloud architects and IT professionals. Future research should explore adaptive explanation generation that tailors both content and presentation to user expertise levels and specific decision contexts. Additionally, evaluation of explanation effectiveness currently relies heavily on subjective user feedback, indicating a need for more objective metrics to assess explanation quality and impact on decision outcomes.

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