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Enhancing Transparency in Cloud-Based Access Control: Analyzing RBAC, ABAC, DLBAC, and XAI Techniques

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Abstract:

Cloud computing has emerged as a dominant paradigm for delivering computing resources on demand, enabling organizations to scale operations rapidly while reducing infrastructure and maintenance costs. Its widespread adoption across sectors such as healthcare, finance, education, and public administration has transformed how digital services are deployed and managed. At the same time, the shared, distributed, and multi-tenant nature of cloud platforms introduces complex security challenges, particularly in access control, where unauthorized or inappropriate access can lead to serious operational and compliance risks. Traditional authorization mechanisms, including Role-Based Access Control (RBAC) and Attribute-Based Access Control (ABAC), provide structured, policy-driven approaches for managing permissions. Although effective in relatively stable environments, these models often lack the adaptability and contextual intelligence required for dynamic cloud ecosystems characterized by changing user behaviour, diverse devices, and evolving threat patterns. Recent advances in Artificial Intelligence (AI), especially Deep Learning–Based Access Control (DLBAC), have improved decision accuracy and enhanced the detection of anomalous access behaviour. However, such AI-driven systems typically operate as black boxes, offering limited insight into how access decisions are made. This opacity raises concerns related to transparency, trust, accountability, auditability, and regulatory compliance. This paper presents a systematic analysis of RBAC, ABAC, and DLBAC models, alongside Explainable Artificial Intelligence (XAI) techniques, including SHAP and LIME. By integrating explainability into access control decision-making, the study identifies pathways toward more transparent, responsible, and trustworthy cloud security architectures that align with modern sustainability and compliance requirements.

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Introduction

Cloud computing has steadily evolved into a core component of today's digital ecosystem, allowing organizations to expand their computing capabilities, optimize operational costs, and deliver services across geographical boundaries. Sectors such as healthcare, finance, education, and public administration now depend heavily on cloud platforms for managing and processing sensitive and mission-critical data. As this dependence grows, ensuring that access to cloud resources is carefully controlled has become a fundamental security requirement.

Over time, several access control models have been developed to address authorization challenges in distributed systems. Role-Based Access Control (RBAC) streamlines permission management by assigning privileges based on predefined roles, while Attribute-Based Access Control (ABAC) enables more granular decision-making through the evaluation of user, resource, and environmental attributes. More recently, Deep Learning–Based Access Control (DLBAC) models have introduced adaptive intelligence by learning from historical access patterns and contextual information. Although each of these approaches offers distinct advantages, they share a notable shortcoming—limited transparency in how access decisions are derived.

In highly dynamic cloud environments, this lack of interpretability can weaken user trust, complicate regulatory compliance, and restrict administrators' ability to audit or justify authorization outcomes. Regulations such as the General Data Protection Regulation (GDPR) and the Health Insurance Portability and Accountability Act (HIPAA) increasingly demand accountability and clarity in automated decision-making. When users are denied access without a clear explanation, it often leads to confusion, diminished confidence in the system, and, in some cases, legal or compliance-related concerns.

Explainable Artificial Intelligence (XAI) has emerged as a practical response to these challenges by offering mechanisms that clarify how intelligent systems reach specific decisions. Methods such as SHapley Additive Explanations (SHAP), Local Interpretable Model-Agnostic Explanations (LIME), and inherently interpretable models like decision trees

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help translate complex AI behaviour into explanations that can be understood by humans. When integrated into access control systems, these techniques enhance not only interpretability but also accountability and audit readiness.

This paper examines traditional and AI-driven access control models, RBAC, ABAC, and DLBAC, alongside prominent XAI techniques to evaluate their individual strengths, limitations, and areas of convergence. By doing so, it aims to demonstrate how explainability can shift cloud access control systems from opaque enforcement mechanisms toward transparent, trustworthy, and sustainable security solutions.

Review of literature

Access control has long been a central concern in secure system design, with early solutions relying on rule-based authorization mechanisms. Among these, Role-Based Access Control (RBAC) emerged as a widely adopted model due to its administrative simplicity and structured design.

Sandhu and Samarati (1994) formalized RBAC by introducing the concept of assigning permissions to roles rather than individual users, thereby reducing management overhead in organizational settings. The model also supports role hierarchies and separation-of-duty constraints, which further enhance policy enforcement in enterprise environments.

Despite its widespread adoption, RBAC has been observed to perform poorly in environments characterized by frequent changes and diverse access contexts. Cloud platforms, in particular, require authorization mechanisms that can adapt to fluctuating workloads, dynamic user behavior, and contextual variations. Several studies have noted that RBAC's static role assignments limit its responsiveness in such scenarios. Additionally, while RBAC decisions are deterministic, the model provides limited explanatory feedback regarding why access is granted or denied, which complicates auditing and compliance verification in regulated domains. To address these limitations, Attribute-Based Access Control (ABAC) was proposed as a more flexible alternative.

Ferraiolo et al. (2001) extended traditional authorization by allowing access decisions to be derived from a combination of attributes related to users, resources, actions, and environmental conditions. This attribute-centric approach enables fine-grained and context-

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aware access control, making ABAC particularly suitable for distributed and cloud-based systems.

Hu et al. (2015), in their NIST standardization work, highlighted ABAC's superior adaptability when compared to role-centric models. However, they also observed that as the number of attributes and policies increases, system administration becomes significantly more complex. In practice, this complexity reduces interpretability, as administrators often find it difficult to identify which attribute combinations influenced a specific decision. Consequently, although ABAC enhances flexibility, it does not fully resolve the transparency challenges present in cloud access control.

From a comparative standpoint, both RBAC and ABAC continue to serve as foundational authorization models. Nevertheless, neither model sufficiently addresses the growing need for clear, user-oriented explanations of access decisions in dynamic cloud environments. This limitation becomes particularly evident when systems are subject to compliance audits or user disputes.

In recent years, researchers have increasingly explored the use of artificial intelligence to overcome the rigidity of traditional access control models. Deep Learning–Based Access Control (DLBAC) represents a shift toward data-driven authorization, where models learn access patterns from historical and contextual information.

Nobi et al. (2022) proposed a convolutional neural network–based framework that classified access requests using parameters such as access time, device characteristics, and prior usage behavior. Their experimental results demonstrated measurable improvements in decision accuracy and a reduction in unauthorized access incidents when compared to RBAC-based systems.

While these findings highlight the potential of deep learning for adaptive security, they also expose a fundamental weakness. The internal reasoning of deep learning models remains largely opaque, making it difficult for administrators or end-users to understand why a particular access request was approved or denied. This lack of interpretability presents challenges in environments where accountability and traceability are required. To improve robustness, ensemble-based approaches have also been proposed.

Wang and Liu (2024) combined multiple machine learning classifiers, including Random Forest and Gradient Boosting, to detect anomalous access behavior in cloud systems. Their

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model achieved high detection accuracy while reducing false positives. Similarly, Akbarfam et al. (2023) integrated blockchain technology with deep learning to support secure access control across multi-cloud environments, providing verifiable audit records alongside anomaly detection.

Despite their technical effectiveness, these intelligent access control systems largely inherit the black-box characteristics of machine learning models.

Neupane et al. (2022) noted that system administrators often prefer slightly less accurate models that provide interpretable decision logic over highly accurate but opaque systems. This preference highlights a persistent trade-off between performance and explainability, reinforcing the need for explainable AI in access control applications. Explainable Artificial Intelligence has gained prominence as a means of addressing the transparency limitations of complex machine learning models.

Arrieta et al. (2020) presented a comprehensive overview of XAI approaches, categorizing them into model-agnostic and model-specific techniques. Among these, post-hoc explanation methods such as Local Interpretable Model-Agnostic Explanations (LIME) and SHapley Additive Explanations (SHAP) have been widely adopted due to their flexibility and applicability across different model types. These techniques interpret predictions by estimating the influence of individual features on a given outcome, thereby offering insights into model behavior without modifying the underlying architecture. However, prior studies caution that post-hoc explanations may introduce approximation errors and computational overhead, particularly in real-time systems. Beyond technical considerations, explainability has also been examined from a human-centric perspective.

Doshi-Velez and Kim (2017) emphasized that explanations should be tailored to the needs of different stakeholders, including developers, auditors, and end-users. Their work underscores the importance of aligning explanation depth and format with user expertise, a factor that is especially relevant in access control systems deployed across organizational hierarchies.

Several recent studies have demonstrated the feasibility of integrating XAI directly into access control frameworks. Angelov et al. (2021) showed that interpretable reasoning could be incorporated into ABAC systems by mapping access decisions to attribute-level explanations. Venturini et al. (2024) introduced CASTLE, a SHAP-based framework designed for large-scale cloud platforms, enabling near real-time explanation of authorization outcomes. Similar results were reported by Smith et al. (2025) in IoT–cloud environments,

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where lightweight XAI models improved transparency without significantly degrading system performance.

The inherent characteristics of cloud environments, such as elasticity, resource sharing, and multi-tenancy, introduce additional complexity for access control systems. Adaptive security mechanisms have therefore been proposed to dynamically adjust permissions based on observed behavior. Wang and Liu (2024) employed reinforcement learning to modify access policies in response to evolving threat patterns, reporting notable improvements in preventing unauthorized access.

Cross-platform evaluations further highlight the benefits and limitations of explainable access control. Lin et al. (2023) benchmarked XAI-enabled policy enforcement mechanisms across major cloud service providers, including AWS and Azure, and observed improvements in scalability and response time when compared to conventional ABAC systems. At the same time, their study noted performance trade-offs, as the inclusion of explainability mechanisms can introduce additional latency.

Privacy considerations also play a critical role. Allana et al. (2025) cautioned that overly detailed explanations may inadvertently disclose sensitive attribute information, thereby increasing system vulnerability. Addressing this concern, Rong et al. (2022) demonstrated that explanation formats tailored to user expertise, such as visual summaries or example-based explanations, significantly improved comprehension while minimizing information exposure.

The expansion of automated decision-making in cloud security has intensified regulatory and ethical scrutiny. Wachter, Mittelstadt, and Floridi (2017) examined the implications of the "right to explanation" under the General Data Protection Regulation (GDPR), arguing that opaque AI systems challenge established principles of fairness and accountability. These concerns are particularly relevant for access control systems that directly affect user rights and data protection.

Building on this perspective, Floridi et al. (2022) proposed the concept of "Ethics by Design," advocating the integration of ethical principles—such as transparency, fairness, and human oversight—throughout the system development lifecycle. Empirical studies support this approach. Smith, O'Reilly, and Zhang (2025) reported that access control systems

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providing clear explanations improved user trust and regulatory compliance by approximately 35% in highly regulated sectors, including healthcare and banking.

Taken together, these findings indicate that explainability is not merely a technical enhancement but a foundational requirement for ethical, lawful, and sustainable cloud-based access control systems.

Table: 1 Summarizes the key strengths, limitations, and transparency characteristics of access control models and explainability approaches discussed in the literature.

Model/Technique	Strengths	Limitations	Transparency Level
RBAC (Sandhu & Samarati, 1994)	Simple, role hierarchies	Static, lacks adaptability	High (rule-based, but limited context)
ABAC (Ferraiolo et al., 2001; Hu et al., 2015)	Fine-grained, flexible	Complex policy management	Moderate
DLBAC (Nobi et al., 2022)	Adaptive, accurate	Black-box, opaque	Low
Ensemble/Hybrid AI (Wang & Liu, 2024; Akbarfam et al., 2023)	High accuracy, anomaly detection	Limited interpretability	Low
XAI (SHAP, LIME, CASTLE, Smith et al., 2025)	Human-readable explanations, compliance support	Performance trade-offs, privacy concerns	High
Ethical/Legal Frameworks (Wachter et al., 2017; Floridi et al., 2022)	Regulatory alignment, trust	Implementation complexity	High

Research Gaps Identified

A review of existing literature reveals persistent limitations in cloud-based access control systems, particularly with respect to transparency and interpretability. While traditional models such as RBAC and ABAC provide structured authorization, and AI-driven

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approaches such as DLBAC enhance adaptability, none adequately explain the rationale behind access decisions in a manner that is understandable to human stakeholders. This limitation directly affects trust, auditability, and regulatory compliance in cloud environments.

A. **Lack of Explainable Access Control Mechanisms**: One significant gap lies in the opaque nature of AI-driven access control mechanisms. Studies have demonstrated that deep learning and ensemble-based models improve detection accuracy and reduce unauthorized access; however, they typically function as black-box systems with minimal insight into decision logic. The absence of explainability restricts accountability and complicates compliance with regulatory requirements such as the GDPR's right to explanation.

B. **Limited integration of Explainable AI techniques into real-time access control pipeline**s: Existing research frequently applies XAI methods in post-hoc or offline settings, reducing their practical value for operational decision-making. Although some efforts have embedded explainability within policy enforcement engines, scalability and performance overhead remain unresolved challenges.

C. **Inadequate Trust and Compliance Support**: The literature further indicates that a lack of transparency negatively impacts trust and system adoption. Empirical studies show that administrators and users often prefer interpretable models over marginal gains in accuracy, particularly in regulated domains. Without meaningful explanations, AI-driven access control systems face resistance and increased compliance complexity.

D. **Scarcity of Adaptive and Transparent Frameworks**: There is a scarcity of unified frameworks that combine adaptive intelligence, real-time enforcement, and explainability within a single, scalable architecture suitable for modern cloud platforms. Existing solutions tend to address these aspects in isolation, limiting their applicability in real-world deployments.

E. **Performance and Privacy Trade-offs**: Unresolved trade-offs between performance, interpretability, and privacy persist. Explainable models may introduce latency or inadvertently expose sensitive attributes, highlighting the need for balanced design strategies.

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These gaps indicate the need for scalable, explainable access control frameworks that integrate AI-driven adaptability with transparency, trust, and regulatory readiness in cloud environments.

Objectives of Research

The primary objective of this study is to analyze existing access control models RBAC, ABAC, and DLBAC and Explainable Artificial Intelligence (XAI) techniques in order to address the challenges of transparency and interpretability in cloud-based access control systems.

To achieve this objective, the study pursues the following specific goals:

1. To critically examine the suitability of traditional access control models, namely RBAC and ABAC, in cloud environments, with particular attention to their adaptability, contextual awareness, and decision transparency.
2. To evaluate AI-driven access control approaches, specifically Deep Learning–Based Access Control (DLBAC), in terms of their adaptability and accuracy, while analyzing the implications of their opaque decision-making for trust, auditing, and regulatory compliance.
3. To study prominent XAI techniques, including SHAP, LIME, decision trees, and hybrid explainability frameworks, and assess their effectiveness in generating human-understandable explanations for access decisions.
4. To explore strategies for integrating explainability into access control frameworks in a manner that balances accuracy, latency, interpretability, and regulatory alignment, thereby enhancing user trust and system accountability.

Research Methodology

This study adopts a structured, multi-phase comparative research methodology to examine transparency and interpretability challenges in cloud-based access control systems and to evaluate the role of Explainable Artificial Intelligence (XAI) techniques in addressing these

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challenges. The methodology integrates systematic literature analysis, conceptual modeling, and metric-based comparison to ensure both academic rigor and practical relevance.

Research Design and Process Flow

The overall research process is organized into seven sequential phases, as illustrated in the process flowchart (Figure 1). The flowchart provides a clear visual representation of how the study progresses from model identification to comparative synthesis, ensuring traceability across all stages of analysis.

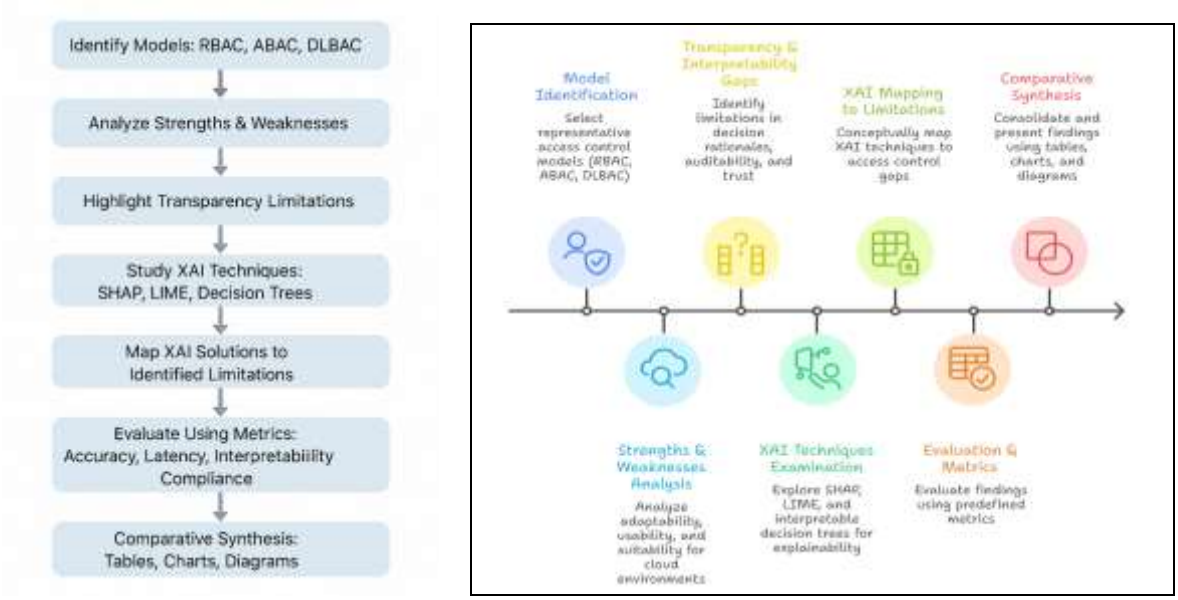

Fig. 1. Research Methodology Process Flowchart

The methodology begins with the identification of representative access control models, namely Role-Based Access Control (RBAC), Attribute-Based Access Control (ABAC), and Deep Learning–Based Access Control (DLBAC), selected due to their widespread adoption and relevance in cloud security literature. This is followed by a systematic analysis of strengths and weaknesses, focusing on adaptability, usability, and suitability for dynamic, context-aware cloud environments.

In the next phase, the study highlights transparency and interpretability limitations inherent in these models, such as the absence of clear decision rationales, limited auditability, and reduced user trust—issues that are particularly pronounced in AI-driven authorization

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mechanisms. Based on these identified gaps, prominent Explainable AI (XAI) techniques, including SHapley Additive Explanations (SHAP), Local Interpretable Model-Agnostic Explanations (LIME), and interpretable decision tree models, are examined to understand their explanatory capabilities.

Subsequently, these XAI techniques are conceptually mapped to the identified limitations of RBAC, ABAC, and DLBAC, emphasizing how explainability can be embedded into access control decision pipelines to enhance transparency without undermining security. The final stages of the methodology involve evaluation using predefined metrics and a comparative synthesis, where findings are consolidated and presented using structured tables, charts, and conceptual diagrams.

Data Sources

The study is grounded in authoritative and peer-reviewed sources, including journal articles, conference proceedings, and technical reports related to access control, cloud security, and explainable AI. In addition, regulatory frameworks such as the General Data Protection Regulation (GDPR), Health Insurance Portability and Accountability Act (HIPAA), and California Consumer Privacy Act (CCPA) are reviewed to contextualize legal requirements for transparency and accountability. Ethical considerations are informed by established principles such as Ethics by Design, which emphasize fairness, accountability, and human oversight in AI-enabled systems.

Evaluation Metrics

The comparative evaluation of access control models and XAI techniques is guided by a clearly defined set of evaluation metrics summarized in Table 2.

Table 2: Evaluation Metrics

METRIC	DESCRIPTION
Accuracy	Correct classification of access requests (Allow/Deny).
Latency	Time taken to process and explain access decisions.
Interpretability	Clarity and comprehensibility of decision rationale for stakeholders.
Compliance Readiness	Alignment with legal mandates like GDPR's "right to explanation."

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User Trust	Confidence and acceptance of AI decisions by administrators and end-users.

These metrics ensure consistent assessment across all phases of the study:

- Accuracy: Measures the correctness of access control decisions, specifically the classification of requests as allow or deny.

- Latency: Captures the time required to process access requests and generate corresponding explanations.
- Interpretability: Assesses the clarity and comprehensibility of decision rationales for administrators, auditors, and end-users.
- Compliance Readiness: Evaluates alignment with regulatory mandates, including the GDPR's "right to explanation" and auditability requirements under HIPAA.
- User Trust: Reflects stakeholder confidence and acceptance of AI-driven authorization decisions, as reported in prior empirical studies.

Methodological Tools and Visualization

To enhance clarity and reproducibility, the methodology employs multiple analytical tools. Comparative tables are used to contrast RBAC, ABAC, DLBAC, and XAI techniques across evaluation metrics. Performance charts visualize trade-offs between accuracy, latency, and interpretability, while conceptual diagrams illustrate potential integration points for XAI within access control workflows. Together, the process flowchart (Figure 1) and the evaluation metrics table (Table 2) form a coherent methodological framework that supports systematic analysis, transparent reasoning, and comparative insight.

Results and Discussion

This section presents the comparative outcomes of the analysis of RBAC, ABAC, DLBAC, and selected Explainable AI (XAI) techniques. The evaluation is structured around five metrics namely accuracy, latency, interpretability, compliance readiness, and user trust. The results are derived from synthesized findings in prior studies and conceptual assessment, offering insights into performance trade-offs and integration potential.

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Comparative Performance Analysis

The comparative evaluation (Table 3) reveals distinct strengths and limitations across traditional, AI-driven, and explainability-enhanced access control approaches.

Table: 3 Comparative Evaluation of Access Control Models and XAI Techniques Across Key Metrics

Model/Technique	Accuracy	Latency	Interpretability	Compliance Readiness	User Trust
RBAC	Moderate	Low	High	Moderate	Moderate
ABAC	High	Moderate	Moderate	Moderate	Moderate
DLBAC	High	High	Low	Low	Low
SHAP (XAI)	High	Moderate	High	High	High
LIME (XAI)	High	Moderate	High	High	High
Decision Trees	Moderate	Low	High	High	High
CASTLE Framework	High	Moderate	High	High	High

1. RBAC demonstrates low latency and high interpretability due to its rule-based structure, but offers only moderate accuracy and limited adaptability in dynamic cloud environments.
2. ABAC achieves higher accuracy than RBAC by incorporating contextual attributes, though increased policy complexity reduces interpretability and administrative clarity.
3. DLBAC consistently outperforms traditional models in accuracy by leveraging behavioral and contextual learning; however, its deep learning architecture results in high latency and minimal transparency, leading to weaker compliance readiness and lower user trust.

In contrast, XAI techniques significantly improve interpretability and compliance alignment when applied either as standalone models or as explanatory layers.

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1. SHAP and LIME provide feature-level explanations that enhance auditability and regulatory alignment while maintaining high predictive performance.
2. Decision tree–based models offer intrinsic transparency and low latency, though with moderate accuracy compared to deep learning approaches.
3. The CASTLE framework balances adaptability and explainability, demonstrating strong performance across all evaluated dimensions.

Overall, models augmented with explainability consistently show higher compliance readiness and user trust than opaque AI-driven systems.

Key Observations

A central finding is the **accuracy–interpretability trade-off**. While DLBAC and ensemble learning models maximize prediction accuracy, they sacrifice transparency, which is critical in regulated cloud environments. Conversely, interpretable models and XAI-enhanced systems offer clearer decision rationales with only marginal reductions in accuracy.

Latency analysis indicates that rule-based systems such as RBAC and decision trees are computationally efficient, whereas deep learning models introduce higher processing overhead. XAI techniques such as SHAP and LIME add moderate explanatory latency but remain feasible for near–real-time access control, particularly when explanations are selectively generated.

From a **compliance perspective**, explainable models demonstrate stronger alignment with regulatory mandates, including the GDPR's "right to explanation" and audit requirements under HIPAA. Systems capable of articulating access decisions in human-understandable terms are better suited for auditing and legal scrutiny.

Finally, **user trust** emerges as a decisive factor. Prior empirical studies consistently indicate that administrators and end-users prefer systems that justify access decisions clearly, even when slight performance trade-offs exist. XAI-enhanced access control models therefore show greater potential for real-world adoption and long-term sustainability.

Accuracy–Interpretability Relationship

The relationship between accuracy and interpretability is summarized conceptually through a performance chart mapping evaluated models across these dimensions

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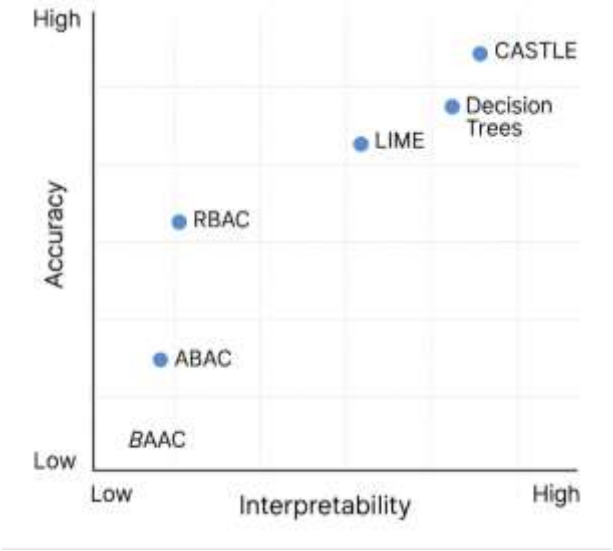

Fig. 1 Accuracy–Interpretability Trade-off among Access Control Models and XAI Techniques

DLBAC occupies the high-accuracy, low-interpretability region, highlighting its black-box nature. In contrast, SHAP-, LIME-, and CASTLE-based approaches cluster in the high-accuracy, high-interpretability region, demonstrating that explainability can coexist with strong predictive performance. RBAC and decision trees lie in the moderate-accuracy, high-interpretability region, reinforcing their suitability for environments prioritizing transparency over adaptiveness.

Integration Implications

The findings suggest that hybrid integration of XAI with existing access control models offers the most practical path forward. Examples include coupling DLBAC with SHAP to explain deep learning outputs, applying LIME to ABAC for localized attribute-based explanations, and enhancing RBAC with decision-tree representations to support visual auditing. Such integrations enable transparent, accountable, and regulation-aware access control without fundamentally redesigning existing cloud security architectures.

Conclusions & Future scope

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The findings presented in the Results and Discussion section demonstrate clear performance distinctions among RBAC, ABAC, and DLBAC when evaluated across accuracy, latency, interpretability, compliance readiness, and user trust. Traditional models such as RBAC and ABAC exhibit low latency and higher interpretability but show limited adaptability in dynamic cloud environments. In contrast, DLBAC achieves superior accuracy and adaptive decision-making capabilities, albeit at the cost of transparency, explainability, and regulatory alignment.

The results further indicate that the integration of Explainable Artificial Intelligence (XAI) techniques such as SHAP, LIME, interpretable decision trees, and hybrid frameworks like CASTLE effectively addresses these limitations. XAI-enhanced models consistently demonstrate improved interpretability and compliance readiness while maintaining competitive accuracy and acceptable latency. This balance is particularly significant for cloud environments operating under regulatory constraints, where explainability and auditability are as critical as predictive performance.

Beyond technical contributions, this work aligns with the principles of sustainable development in engineering and technology. Transparent and explainable access control systems promote ethical AI adoption, responsible governance, and long-term resilience of digital infrastructures. By fostering accountability and trust, such systems contribute to sustainable cloud ecosystems that can safely support critical services across sectors such as healthcare, finance, education, and governance.

Future Scope

Building on the findings of this study, several avenues for future research are identified:

- Privacy-Preserving Explainability

  Future work can focus on designing XAI mechanisms that provide meaningful explanations without exposing sensitive attributes or increasing security risks.
- Real-Time Explainable Access Control

  Integrating XAI directly into live access control engines remains an open challenge, particularly in achieving real-time explanations without introducing unacceptable latency.
- Extension to Edge and IoT Environments

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The proposed concepts can be adapted for edge-cloud and IoT ecosystems, where lightweight, interpretable models are essential for low-latency and resource-constrained settings.

- User-Centric Explanation Design

  Further studies may explore explanation formats tailored to different stakeholders—administrators, auditors, and end-users—to improve comprehension and trust across diverse user groups.

- Ethics-by-Design Frameworks

  Embedding ethical principles such as fairness, accountability, and human oversight into access control architectures offers a promising direction for responsible AI-driven security systems.

- Cross-Platform Benchmarking

  Empirical evaluation of explainable access control frameworks across major cloud platforms such as AWS, Azure, and Kubernetes would help validate scalability, compliance readiness, and practical adoption.

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