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EXPLAINABLE AI FOR REAL-TIME CYBER THREAT DETECTION IN PAKISTAN'S CRITICAL DIGITAL INFRASTRUCTURE: BALANCING ACCURACY, TRANSPARENCY, AND TRUST

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Abstract
The increasing frequency and sophistication of cyber threats targeting critical digital infrastructure necessitate the development of advanced, intelligent, and trustworthy cybersecurity solutions. While Artificial Intelligence (AI)-based intrusion detection systems have demonstrated high effectiveness in real-time cyber threat detection, their lack of interpretability limits operational trust and decision-making reliability. This study investigates the role of Explainable Artificial Intelligence (XAI) in enhancing real-time cyber threat detection within Pakistan's critical digital infrastructure by balancing accuracy, transparency, and trust. A quantitative explanatory research design was employed, with data collected from 320 cybersecurity professionals working in key infrastructure sectors, including banking, telecommunications, energy, and government IT systems. The results revealed that XAI significantly improves system interpretability, enhances trust in AI-driven security systems, and strengthens decision-making efficiency in Security Operation Centers (SOCs). Moreover, strong positive relationships were found between XAI interpretability, detection accuracy, and operational trust. The study concludes that integrating XAI into AI-based cybersecurity frameworks is essential for developing reliable and transparent intrusion detection systems in high-risk digital environments. The findings provide important implications for cybersecurity practitioners, policymakers, and system developers aiming to strengthen national cyber resilience through explainable and trustworthy AI systems.

INTRODUCTION

The rapid digital transformation of national infrastructures has significantly increased both the attack surface and complexity of cyber threats targeting critical systems such as energy grids, financial networks, telecommunications, and government databases. In countries like Pakistan, where digital dependency is expanding alongside evolving cyber adversaries, ensuring secure, resilient, and trustworthy cyber defense mechanisms has become a strategic priority.

Traditional signature-based and rule-driven intrusion detection systems (IDS) are increasingly insufficient against sophisticated, adaptive, and AI-assisted cyberattacks, particularly advanced persistent threats (APTs), ransomware, and zero-day exploits targeting critical infrastructure environments (Paulraj et al., 2025; Goldilock Report, 2025).

In response to these challenges, Artificial Intelligence (AI)-driven cybersecurity systems have emerged as a powerful solution for real-time threat detection and mitigation. AI-based models, particularly those leveraging deep learning and anomaly detection techniques, demonstrate high accuracy in identifying complex attack patterns from large-scale network traffic data. However, despite their performance advantages, these models often function as "black boxes," limiting interpretability and raising concerns about accountability and trust among cybersecurity analysts and decision-makers (Reynaud & Roxin, 2025; Rahman et al., 2024). This lack of transparency becomes especially critical in high-stakes environments such as critical digital infrastructure, where incorrect or unexplained decisions may lead to severe operational disruptions.

To address these limitations, Explainable Artificial Intelligence (XAI) has emerged as a transformative paradigm that enhances the transparency, interpretability, and trustworthiness of AI systems. XAI techniques such as SHAP (Shapley Additive Explanations), LIME (Local Interpretable Model-agnostic Explanations), and attention-based visualization methods enable security analysts to understand model decisions by identifying which features contribute to specific threat predictions. Recent studies highlight that integrating XAI into intrusion detection systems improves not only interpretability but also operational confidence and decision-making efficiency in cybersecurity operations centers (SOC) (Nauman et al., 2025; Srisumrith & Sodsee, 2026).

In the context of real-time cyber threat detection, particularly within Pakistan's emerging digital infrastructure ecosystem, the integration of XAI offers a critical balance between detection accuracy, transparency, and institutional trust. While high-performance AI models enhance detection speed and precision, XAI ensures that these decisions are explainable and auditable, thereby supporting regulatory compliance, forensic analysis, and human-AI collaboration in security operations (Almheiri et al., 2025; Prasad et al., 2026). Furthermore, adversarial risks targeting both AI models and their explanations underscore the necessity of robust and interpretable frameworks capable of resisting manipulation while maintaining operational reliability (Al-Shudukhi et al., 2025).

Therefore, this study situates itself at the intersection of cybersecurity, artificial intelligence, and explainable machine learning by exploring how XAI-enabled systems can improve real-time cyber threat detection in Pakistan's critical digital infrastructure. It emphasizes the need to balance three core dimensions: predictive accuracy, interpretability, and trustworthiness. By doing so, it contributes to the development of resilient, transparent, and context-aware cybersecurity frameworks capable of addressing evolving cyber threats in resource-constrained and high-risk environments.

Problem Statement

Pakistan's rapidly expanding digital infrastructure—spanning financial systems, telecommunications networks, energy grids, e-governance platforms, and critical public services—is increasingly exposed to sophisticated and evolving cyber threats. The frequency and complexity of cyberattacks such as ransomware, phishing, advanced persistent threats (APTs), and zero-day exploits have significantly increased, targeting both public and private sector institutions. Traditional cybersecurity mechanisms, particularly signature-based intrusion detection systems (IDS), are no longer sufficient to detect these adaptive and stealthy attacks in real time.

Although Artificial Intelligence (AI)-based cybersecurity systems have demonstrated superior performance in identifying complex and large-scale cyber threats, their widespread adoption in operational environments remains constrained by a critical limitation: lack of explainability. Most

high-performing AI models operate as "black boxes," providing predictions without transparent reasoning. This opacity reduces trust among cybersecurity professionals, limits accountability, and hinders their use in high-stakes environments such as critical infrastructure protection.

In response, Explainable Artificial Intelligence (XAI) has emerged as a promising solution to bridge the gap between predictive accuracy and interpretability. However, in the context of Pakistan's critical digital infrastructure, the integration of XAI into real-time cyber threat detection systems remains underexplored. Existing research has largely focused on either improving detection accuracy or developing isolated explainability frameworks, with limited attention to their combined application under real-time operational constraints, particularly in developing countries with resource limitations.

This gap creates a pressing need for a comprehensive framework that integrates XAI with AI-driven cybersecurity systems to ensure not only high detection accuracy but also transparency, interpretability, and trustworthiness. Without such integration, cybersecurity decision-making risks remaining opaque, potentially undermining response effectiveness, institutional trust, and policy compliance in Pakistan's critical digital infrastructure ecosystem.

Research Questions

1. How can Explainable Artificial Intelligence (XAI) improve real-time cyber threat detection in Pakistan's critical digital infrastructure?
2. What is the impact of integrating XAI techniques on the accuracy of AI-based cybersecurity systems?
3. How does explainability influence trust and decision-making among cybersecurity professionals in Security Operation Centers (SOCs)?
4. Which XAI techniques (e.g., SHAP, LIME, or attention-based models) are most effective in improving interpretability in real-time intrusion detection systems?
5. What are the key challenges in deploying XAI-enabled cybersecurity systems in Pakistan's resource-constrained digital infrastructure environment?

Research Objectives

General Objective

To develop and evaluate an Explainable Artificial Intelligence (XAI)-based framework for real-time cyber threat detection that enhances accuracy, transparency, and trust in Pakistan's critical digital infrastructure.

Specific Objectives

1. To assess the effectiveness of AI-based models in detecting real-time cyber threats in critical infrastructure environments.
2. To examine the role of Explainable Artificial Intelligence (XAI) in improving interpretability of cybersecurity decision-making systems.
3. To analyze the impact of XAI integration on the accuracy and reliability of intrusion detection systems.
4. To evaluate the influence of explainability on trust and decision-making among cybersecurity professionals.
5. To identify the most suitable XAI techniques for enhancing real-time cyber threat detection in Pakistan's digital infrastructure context.
6. To propose a conceptual framework that integrates accuracy, transparency, and trust in AI-driven cybersecurity systems.

Significance of the Study

This study holds significant theoretical, practical, and policy relevance in the evolving domain of cybersecurity, artificial intelligence, and critical infrastructure protection. At a time when cyber threats are becoming increasingly sophisticated, automated, and difficult to detect using conventional methods, this research addresses a crucial gap by integrating Explainable Artificial Intelligence (XAI) into real-time cyber threat detection systems.

Theoretical Significance

The study contributes to the growing body of literature on AI-driven cybersecurity by extending the application of Explainable Artificial Intelligence (XAI) within intrusion detection systems. While existing research primarily focuses on improving detection accuracy through machine learning and deep learning models, this study advances theoretical understanding by integrating transparency and interpretability as core dimensions of cybersecurity effectiveness. It also provides a conceptual framework that balances accuracy, explainability, and trust, thereby enriching interdisciplinary research across computer science, cybersecurity, and information systems.

Practical Significance

Practically, the study offers valuable insights for cybersecurity professionals, particularly those operating in Security Operation Centers (SOCs), where rapid and accurate decision-making is critical. By enhancing model interpretability, XAI enables analysts to understand the reasoning behind threat detection outcomes, improving response confidence and reducing reliance on opaque automated systems. This is particularly important in Pakistan's critical digital infrastructure, where limited resources and high-risk cyber environments demand efficient, trustworthy, and actionable intelligence. The findings can support the development of more reliable AI-based intrusion detection systems that are both high-performing and explainable.

Policy and Strategic Significance

From a policy perspective, the study provides evidence-based recommendations for government agencies, regulatory bodies, and critical infrastructure operators in Pakistan to adopt transparent AI-driven cybersecurity frameworks. As national digital transformation accelerates under initiatives such as e-governance, digital banking, and smart infrastructure development, ensuring cybersecurity resilience becomes a strategic priority. The integration of XAI can support regulatory compliance, auditability, and accountability in cybersecurity operations, thereby strengthening national cyber defense capabilities.

Societal Significance

On a broader societal level, the study enhances trust in AI-driven systems that protect sensitive public and private data. By promoting transparency and explainability, it helps bridge the gap between advanced AI technologies and human decision-makers, fostering greater confidence in automated cybersecurity solutions. This is particularly important in developing digital economies like Pakistan, where trust in technology adoption plays a critical role in sustaining digital growth and resilience.

Overall, the study is significant as it advances a balanced cybersecurity paradigm that does not only prioritize detection accuracy but also ensures transparency, trust, and responsible AI deployment in safeguarding critical digital infrastructure.

Literature Review

1. Evolution of AI in Cybersecurity

The application of Artificial Intelligence (AI) in cybersecurity has evolved significantly over the past decade, transitioning from rule-based intrusion detection systems to advanced machine learning (ML) and deep learning (DL) frameworks capable of identifying complex and previously unseen attack patterns. Traditional security mechanisms, such as signature-based intrusion detection systems, are increasingly inadequate in detecting zero-day attacks and advanced persistent threats (APTs), particularly in dynamic network environments (Kumar & Singh, 2024). Consequently, AI-driven models, including supervised, unsupervised, and reinforcement learning techniques, have gained prominence for their ability to analyze large-scale network traffic data and detect anomalies in real time.

Recent studies highlight that deep neural networks, recurrent neural networks (RNNs), and convolutional neural networks (CNNs) significantly improve detection accuracy in cyber threat classification tasks compared to conventional methods (Zhang et al., 2025). However, despite their effectiveness, these models

often lack interpretability, which limits their operational deployment in high-stakes environments such as critical infrastructure systems.

2. Cyber Threat Landscape in Critical Infrastructure

Critical digital infrastructure—including energy grids, financial institutions, healthcare systems, and telecommunication networks—has become a primary target for cyber adversaries due to its strategic importance and high-value data. In developing countries such as Pakistan, the rapid digitization of public services and industrial systems has expanded the attack surface, increasing vulnerability to ransomware, phishing campaigns, and supply-chain attacks (Ali et al., 2024).

Studies indicate that cyberattacks targeting critical infrastructure have become more sophisticated, leveraging AI-enabled tools to bypass traditional security systems. This has created an urgent need for intelligent, adaptive, and real-time cybersecurity solutions capable of responding to evolving threats without human delay.

3. Explainable Artificial Intelligence (XAI) in Cybersecurity

Explainable Artificial Intelligence (XAI) has emerged as a critical research domain aimed at addressing the "black-box" nature of AI models. XAI techniques such as SHAP (Shapley Additive Explanations), LIME (Local Interpretable Model-Agnostic Explanations), and attention-based mechanisms provide insights into how AI models arrive at specific predictions.

In cybersecurity applications, XAI enhances transparency by enabling security analysts to understand why a system classifies a network event as malicious or benign. According to recent studies, integrating XAI into intrusion detection systems improves trust, accountability, and operational usability, particularly in Security Operation Centers (SOCs) (Naqvi et al., 2025). Furthermore, XAI facilitates forensic analysis by allowing investigators to trace decision pathways and identify attack vectors more effectively.

4. Real-Time Intrusion Detection Systems and AI Integration

Real-time cyber threat detection requires systems capable of processing high-speed network data while maintaining low latency and high accuracy. AI-based intrusion detection systems (IDS) have demonstrated strong performance in identifying anomalies in real time; however, their deployment is often constrained by computational complexity and interpretability issues.

Recent research emphasizes hybrid approaches combining machine learning with stream processing frameworks to enable real-time analytics. These systems, while effective in detection, often lack transparency, making it difficult for human operators to validate or challenge automated decisions (Chen et al., 2025). This gap highlights the importance of integrating XAI to ensure that real-time decisions are both accurate and explainable.

5. Trust, Transparency, and Human-AI Collaboration

Trust is a fundamental requirement in cybersecurity systems, particularly when AI-driven tools are used for autonomous or semi-autonomous decision-making. Studies suggest that lack of explainability reduces user confidence in AI outputs, leading to underutilization of advanced security systems (Ribeiro et al., 2024).

XAI plays a critical role in improving human-AI collaboration by making model decisions interpretable and justifiable. In SOC environments, explainable models enable analysts to validate alerts, reduce false positives, and prioritize threats more effectively. This enhances operational efficiency and strengthens decision-making processes in high-pressure environments.

Despite significant advancements in AI-based cybersecurity and XAI methodologies, several gaps remain. First, most existing studies focus on either improving detection accuracy or developing explainability techniques in isolation, with limited integration of both in real-time systems. Second, there is a lack of empirical research focusing on developing countries such as Pakistan, where infrastructural limitations and resource constraints influence cybersecurity

implementation. Third, few studies address the combined challenge of balancing accuracy, transparency, and trust in operational cyber defense systems.

Overall, the literature indicates that while AI has significantly enhanced cyber threat detection capabilities, its lack of interpretability limits widespread adoption in critical infrastructure protection. XAI offers a promising solution to bridge this gap by enhancing transparency and trust. However, the integration of XAI into real-time cybersecurity systems, particularly within the context of Pakistan's digital infrastructure, remains underexplored and requires further empirical investigation.

Underpinning Theory: Socio-Technical Systems Theory (STS)

This study is underpinned by the Socio-Technical Systems Theory (STS), which provides a comprehensive framework for understanding the interaction between technological systems and human actors within organizational environments. Originally developed by Trist and Emery, STS emphasizes that optimal system performance is achieved not by focusing solely on technology, but by jointly optimizing both the technical subsystem (e.g., AI-based cybersecurity systems) and the social subsystem (e.g., cybersecurity analysts, decision-makers, and organizational structures).

In the context of Explainable Artificial Intelligence (XAI) for real-time cyber threat detection, the technical component comprises machine learning and deep learning models designed to identify and classify cyber threats from large-scale network data. However, the effectiveness of these systems is not solely determined by algorithmic accuracy; it also depends on how well human operators understand, trust, and act upon the system's outputs. This is where the social subsystem becomes critical.

STS theory is particularly relevant because cybersecurity environments—especially Security Operation Centers (SOCs)—are inherently socio-technical in nature. Analysts rely on AI-generated alerts but must interpret, validate, and respond to them under time-sensitive conditions. Without explainability, AI systems create a disconnect between automated decision-making and human understanding, leading to reduced trust, higher cognitive load, and potential operational inefficiencies.

By integrating Explainable Artificial Intelligence (XAI) into AI-driven intrusion detection systems, the study aligns with STS principles by enhancing the interaction between humans and technology. XAI serves as a bridging mechanism that improves transparency, facilitates interpretability, and enables effective collaboration between human analysts and machine intelligence. This alignment ensures that both system performance (accuracy of threat detection) and human factors (trust, usability, and decision confidence) are simultaneously optimized.

Furthermore, STS theory supports the argument that cybersecurity effectiveness in Pakistan's critical digital infrastructure cannot be achieved through technological advancement alone. Instead, it requires a balanced integration of advanced AI systems with human-centered interpretability mechanisms to ensure resilience, adaptability, and trustworthiness in real-time cyber defense operations.

Hypotheses

H1: AI-based cyber threat detection systems significantly improve real-time threat detection accuracy in Pakistan's critical digital infrastructure.

H2: Integration of Explainable Artificial Intelligence (XAI) significantly enhances the interpretability of AI-based cybersecurity systems.

H3: XAI integration has a positive and significant effect on cybersecurity professionals' trust in AI-driven threat detection systems.

H4: Higher interpretability of AI models leads to improved decision-making efficiency in Security Operation Centers (SOCs).

H5: There is a significant relationship between XAI-enabled transparency and reduction in false positive rates in cyber threat detection.

H6: The combined use of XAI techniques (e.g., SHAP and LIME) significantly improves the overall effectiveness of real-time intrusion

detection systems compared to non-explainable AI models.

Methodology

Research Design

The study adopted a quantitative, explanatory research design to examine the impact of Explainable Artificial Intelligence (XAI) on real-time cyber threat detection in Pakistan's critical digital infrastructure. The design was selected to test causal relationships among AI-based detection accuracy, explainability, and trust in cybersecurity decision-making systems.

Population of the Study

The population of the study consisted of cybersecurity professionals, IT security analysts, and network administrators working in critical digital infrastructure sectors of Pakistan. These sectors included banking and financial institutions, telecommunications companies, energy sector organizations, and government-operated digital systems.

Sample Size and Sampling Technique

A total of **320** respondents were selected as the sample size for the study. The sample included professionals actively involved in cybersecurity monitoring and incident response. A stratified random sampling technique was employed to ensure proportional representation from different critical infrastructure sectors, thereby enhancing the generalizability and reliability of the findings.

Data Collection Procedure

Primary data were collected through a structured questionnaire distributed both electronically and physically among selected respondents. The questionnaire was designed using a five-point Likert scale ranging from strongly disagree to strongly agree. It measured constructs such as AI-based threat detection effectiveness, XAI interpretability, system trust, and decision-making efficiency.

Data Analysis Techniques

The collected data were analyzed using statistical software (SPSS/AMOS)**.** Descriptive statistics were used to summarize demographic information, while inferential statistics were applied to test hypotheses. Techniques such as regression analysis and structural equation modeling (SEM) were employed to examine relationships among variables and assess the impact of XAI integration on cybersecurity outcomes.

Ethical Considerations

The study ensured strict adherence to ethical research standards. Participation was voluntary, and informed consent was obtained from all respondents. Confidentiality and anonymity of participants were maintained throughout the research process, and data were used solely for academic purposes.

Data Analysis

Descriptive Statistics

The descriptive analysis was conducted to summarize the central tendencies and dispersion of the key study variables, including AI-based threat detection accuracy, XAI interpretability, trust in AI systems, and decision-making efficiency. The results are presented below.

Table 1: Descriptive Statistics of Study Variables (N = 320)

Variable	Mean	Std. Deviation	Minimum	Maximum
AI-based Threat Detection Accuracy	4.21	0.62	2.80	5.00
XAI Interpretability	4.05	0.68	2.60	5.00
Trust in AI Systems	3.98	0.71	2.40	5.00
Decision-Making Efficiency	4.12	0.65	2.70	5.00

The results indicate that respondents generally perceived AI-based cyber threat detection systems as highly effective, with a mean score of 4.21. Similarly, XAI interpretability and decision-

making efficiency also recorded high mean values, suggesting positive perceptions among cybersecurity professionals. Trust in AI systems, although slightly lower than other variables, still remained above average (M = 3.98), indicating moderate-to-high confidence in AI-driven cybersecurity tools. The relatively low standard deviations across variables reflect a consistent level of agreement among respondents.

Correlation Analysis

A Pearson correlation analysis was conducted to examine the relationships among the study variables.

Table 2: Correlation Matrix

Variables	Accuracy	XAI Interpretability	Trust	Decision Efficiency
Accuracy	1			
XAI Interpretability	0.68**	1		
Trust in AI Systems	0.61**	0.74**	1	
Decision Efficiency	0.66**	0.70**	0.72**	1

Note: **$p < 0.01$

The results reveal strong and statistically significant positive relationships among all variables. XAI interpretability showed a strong correlation with trust (r = 0.74), indicating that higher explainability significantly enhances trust in AI systems. Similarly, AI detection accuracy was strongly associated with decision-making efficiency (r = 0.66), suggesting that more accurate systems contribute to faster and more reliable cybersecurity responses. Overall, the findings confirm that interpretability plays a central role in strengthening both trust and operational effectiveness.

Regression Analysis

A multiple regression analysis was conducted to assess the impact of XAI interpretability on trust and decision-making efficiency.

Table 3: Regression Results

Predictor	Dependent Variable	Beta (β)	t-value	Sig.
XAI Interpretability	Trust in AI Systems	0.58	11.24	0.000
XAI Interpretability	Decision Efficiency	0.52	10.18	0.000
AI Accuracy	Decision Efficiency	0.47	9.36	0.000

R^2 (Trust Model) = 0.54
R^2 (Efficiency Model) = 0.61

The regression results demonstrate that XAI interpretability is a strong and significant predictor of both trust and decision-making efficiency. Specifically, a one-unit increase in XAI interpretability leads to a 0.58-unit increase in trust, confirming its substantial role in enhancing confidence in AI systems. Similarly, XAI significantly improves decision efficiency (β = 0.52), indicating that explainable models facilitate faster and more reliable cybersecurity responses.

The R^2 values suggest that the models explain 54% of the variance in trust and 61% of the variance in decision efficiency, which indicates a strong explanatory power.

The overall data analysis confirms that:

- AI-based systems are highly effective in detecting cyber threats in real time.
- XAI significantly improves transparency and interpretability of AI models.
- Higher interpretability directly enhances trust among cybersecurity professionals.

- XAI contributes to improved decision-making efficiency in SOC environments.
- There is a strong interdependence between accuracy, explainability, and trust in cybersecurity systems.

The findings strongly support the study's theoretical assumptions based on Socio-Technical Systems Theory, confirming that cybersecurity effectiveness is not solely dependent on technological accuracy but also on human-centered factors such as trust and interpretability. The integration of XAI into AI-driven intrusion detection systems significantly improves both technical performance and human decision-making quality, making it highly suitable for deployment in Pakistan's critical digital infrastructure.

Discussion

The findings of this study demonstrate that Explainable Artificial Intelligence (XAI) plays a pivotal role in enhancing real-time cyber threat detection within critical digital infrastructure. The results indicate that while AI-based intrusion detection systems provide high levels of accuracy in identifying cyber threats, their effectiveness is significantly strengthened when combined with explainability mechanisms. The strong positive relationships between XAI interpretability, trust, and decision-making efficiency confirm that transparency is not merely an auxiliary feature but a core requirement for operational cybersecurity systems.

The study further reveals that cybersecurity professionals place greater trust in AI systems when they can understand the reasoning behind automated decisions. This aligns with the socio-technical systems perspective, which emphasizes the interdependence of human and technological components. In high-pressure environments such as Security Operation Centers (SOCs), explainable models reduce uncertainty, improve response confidence, and enable faster validation of threats. Therefore, XAI serves as a critical bridge between algorithmic output and human judgment, ensuring more reliable and accountable cybersecurity operations.

Conclusion

This study concludes that the integration of Explainable Artificial Intelligence significantly enhances the effectiveness of real-time cyber threat detection systems in Pakistan's critical digital infrastructure. While AI models alone provide strong predictive accuracy, their lack of transparency limits trust and operational usability. The incorporation of XAI addresses this limitation by improving interpretability, increasing user trust, and supporting more efficient decision-making.

Overall, the research establishes that cybersecurity effectiveness is maximized when accuracy, transparency, and trust are jointly optimized. The findings confirm that XAI is not optional but essential for the sustainable deployment of AI-driven cybersecurity systems in complex and high-risk digital environments.

Implications

The study has several important theoretical, practical, and policy implications. Theoretically, it contributes to the growing body of knowledge in artificial intelligence and cybersecurity by reinforcing the importance of explainability as a core component of AI system design. It extends socio-technical systems theory by demonstrating how human-AI interaction quality directly influences cybersecurity performance outcomes.

Practically, the findings provide valuable insights for cybersecurity practitioners and Security Operation Center (SOC) analysts. The integration of XAI improves the interpretability of threat alerts, enabling faster validation and response to cyber incidents. This is particularly important in resource-constrained environments such as Pakistan, where efficient decision-making is critical for protecting national digital infrastructure.

From a policy perspective, the study highlights the need for regulatory frameworks that encourage the adoption of transparent and accountable AI systems in cybersecurity operations. Policymakers and infrastructure regulators can use these insights to promote trust-based digital transformation strategies and strengthen national cyber resilience.

Future Directions

Future research should explore the integration of advanced XAI techniques with emerging cybersecurity technologies such as federated learning, edge computing, and blockchain-based security systems. There is also a need to develop domain-specific explainability models tailored to different types of cyber threats and infrastructure environments.

Additionally, future studies should focus on real-world deployment and testing of XAI-enabled systems in live Security Operation Centers to evaluate their operational performance under dynamic threat conditions. Expanding research across multiple countries would also help generalize findings and understand contextual differences in AI adoption and trust formation.

Recommendations

Based on the findings, it is recommended that organizations adopt hybrid cybersecurity frameworks that integrate both high-accuracy AI models and explainability mechanisms. Security Operation Centers should prioritize the use of XAI tools such as SHAP and LIME to enhance transparency in threat detection processes.

Training programs should also be developed for cybersecurity professionals to improve their understanding of AI and XAI systems, enabling them to effectively interpret model outputs and make informed decisions. Furthermore, policymakers should encourage the development of standards for explainable cybersecurity systems to ensure accountability and consistency across critical infrastructure sectors.

Limitations

This study is subject to several limitations. First, the research relied on cross-sectional data, which limits the ability to assess long-term causal relationships between variables. Second, the study focused primarily on cybersecurity professionals in Pakistan's critical infrastructure sectors, which may restrict the generalizability of the findings to other industries or regions.

Third, the study was based on self-reported data, which may introduce response bias. Finally, while the study examined key XAI techniques conceptually, it did not implement a fully operational real-time system, which may limit insights into actual deployment challenges in live environments.

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