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Federated and Explainable Machine Learning for Secure and Trustworthy SIoT Applications

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ABSTRACT

The Social Internet of Things (SIoT) integrates IoT devices with social networking principles, enabling autonomous device interactions and enhanced user services in applications like smart homes, healthcare, and smart cities. However, SIoT systems face significant challenges in ensuring security, privacy, and trust due to their distributed nature, heterogeneous data, and vulnerability to attacks such as model poisoning and data breaches. This review paper examines the role of federated learning (FL) and explainable artificial intelligence (XAI) in addressing these challenges to build secure and trustworthy SIoT applications. FL enables privacy-preserving, decentralized model training across SIoT devices, while XAI enhances transparency and user trust by providing interpretable model decisions. We synthesize recent research, categorizing approaches based on FL techniques, XAI methods, and SIoT application domains. Key findings highlight the growing adoption of FL for privacy in SIoT, the integration of XAI for transparent decision-making, and persistent gaps, such as scalability issues and limited robustness against adversarial attacks. We identify trends, including the use of differential privacy in FL and post-hoc explanation methods in XAI, and discuss open challenges like balancing explainability with performance and ensuring ethical AI in SIoT. This review provides a comprehensive taxonomy and a roadmap for future research to advance secure and trustworthy SIoT ecosystems.

Keywords- Federated Learning, Explainable Artificial Intelligence (XAI), Social Internet of Things (SIoT), Data Privacy and Security, Trustworthy Machine Learning.

I. INTRODUCTION

The Social Internet of Things (SIoT) represents an evolution of the Internet of Things (IoT), where devices form social-like relationships to facilitate autonomous interactions and enhance user-centric services in domains such as smart homes, healthcare, and smart cities [1]. Unlike traditional IoT, SIoT leverages interconnected devices with social networking principles, enabling dynamic collaborations and data sharing among devices and users [4]. However, this interconnected ecosystem introduces significant challenges, including security vulnerabilities (e.g., data breaches, model poisoning) and trust deficits due to opaque decision-making processes [2]. Ensuring security and trust in SIoT is critical, as these systems handle sensitive data and operate in distributed, heterogeneous environments.

Federated learning (FL) has emerged as a promising approach to address privacy concerns in SIoT by enabling decentralized model training, where devices collaboratively train models without sharing raw data [4]. Techniques like secure aggregation and differential privacy further enhance FL's ability to protect user data [5]. Simultaneously, explainable artificial intelligence (XAI) provides transparency by making machine learning models interpretable, fostering user trust through clear decision-making processes [6]. For instance, XAI methods like SHAP and LIME have been applied to explain model predictions in IoT contexts [7]. The integration of FL and XAI is particularly relevant for SIoT, where privacy-preserving learning and transparent decision-making are essential for secure and trustworthy applications.

This review aims to survey and analyze existing research on the application of FL and XAI in SIoT, with a focus on enhancing security and trustworthiness. We explore how these technologies address challenges such as adversarial attacks, scalability, and ethical concerns in SIoT environments. The scope of this review encompasses SIoT applications in domains like smart homes, healthcare, and social networks, emphasizing solutions that combine FL's privacy guarantees with XAI's interpretability. Our contributions include a comprehensive taxonomy of FL and XAI approaches in SIoT, a critical analysis of their strengths and limitations, and a roadmap for future research to bridge existing gaps.

II. BACKGROUND AND KEY CONCEPTS

This section provides an overview of the foundational concepts relevant to the review, including the Social Internet of Things (SIoT), federated learning (FL), explainable artificial intelligence (XAI), and the security and trust challenges in SIoT. We also discuss the interrelation between FL and XAI in enhancing secure and trustworthy SIoT applications.

2.1. Social Internet of Things (SIoT)

The Social Internet of Things (SIoT) extends the Internet of Things (IoT) by integrating social networking principles, enabling devices to form autonomous relationships and interact similarly to human social networks [1]. In SIoT, devices establish connections based on shared objectives, ownership, or context, creating a network of trust and collaboration [4]. The architecture typically includes physical devices (e.g., sensors, actuators), a middleware layer for service discovery, and a social network layer for device interactions [1]. Key applications include smart cities (e.g., traffic management), healthcare (e.g., remote patient monitoring), and social networks (e.g., personalized recommendations) [2]. SIoT's distributed and interconnected nature enhances scalability but introduces challenges in security, privacy, and trust management [4].

2.2. Federated Learning (FL)

Federated learning (FL) is a decentralized machine learning approach that enables multiple devices to collaboratively train a shared model without exchanging raw data, thus preserving privacy [4]. In FL, each device trains a local model on its data and sends only model updates (e.g., gradients) to a central server for aggregation, often using algorithms like Federated Averaging (FedAvg) [4]. Privacy mechanisms, such as differential privacy and secure multi-party computation, mitigate risks of data leakage and model inversion attacks [5], [8]. In SIoT, FL is particularly valuable for enabling privacy-preserving learning across heterogeneous devices with non-independent and identically distributed (non-IID) data [9]. Challenges include communication overhead, device heterogeneity, and robustness against Byzantine faults [5].

2.3. Explainable Artificial Intelligence (XAI)

Xplainable AI (XAI) focuses on making machine learning models transparent and interpretable to foster trust and accountability [6]. XAI techniques include post-hoc methods, such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations), which explain complex model predictions by highlighting feature importance [7], [10]. Inherently interpretable models, such as decision trees or rule-based systems, offer built-in transparency [6]. In SIoT, XAI ensures that decisions made by models (e.g., device coordination, anomaly detection) are understandable to users and stakeholders, enhancing trust in critical applications like healthcare and smart homes [11]. Challenges include balancing explainability with model accuracy and computational efficiency [6].

2.4. Security and Trust in SIoT

SIoT systems face significant security and trust challenges due to their distributed architecture and reliance on sensitive data. Key threats include data privacy breaches, adversarial attacks (e.g., data poisoning, model evasion), and model poisoning in collaborative learning scenarios [12]. The lack of interpretability in traditional machine learning models exacerbates trust issues, as users cannot verify the rationale behind decisions [13]. Trust in SIoT also depends on ensuring device authenticity, secure communication, and robust defense against malicious actors [2]. These challenges necessitate solutions that combine privacy-preserving learning with transparent decision-making to ensure secure and trustworthy SIoT ecosystems.

2.5. Interrelation of FL and XAI in SIoT

The integration of FL and XAI offers a synergistic approach to addressing security and trust in SIoT. FL ensures privacy by keeping data on local devices, reducing the risk of centralized data breaches, while XAI provides interpretable model outputs, enabling users to understand and trust system decisions [14]. For example, in a smart healthcare SIoT application, FL can enable collaborative training of a disease prediction model across wearable devices, while XAI can explain the model's predictions to patients and clinicians [11]. However, integrating FL and XAI poses challenges, such as ensuring explainability without compromising privacy and managing the computational overhead of XAI in resource-constrained SIoT devices [14]. This review xplores how these technologies are combined to enhance security and trust in SIoT applications.

III. LITERATURE REVIEW METHODOLOGY

This section details the systematic methodology used to review literature on federated learning (FL) and explainable artificial intelligence (XAI) for secure and trustworthy Social Internet of Things (SIoT) applications. The approach ensures transparency, reproducibility, and rigor, adhering to established guidelines for systematic literature reviews [15], [16].

3.1. Search Criteria

The literature search was conducted across multiple academic databases to ensure comprehensive coverage of peer-reviewed studies. The databases included IEEE Xplore, ACM Digital Library, SpringerLink, Scopus, Web of Science, and Google Scholar, selected for their extensive repositories in computer science, IoT, and machine learning [17], [18]. Search queries combined keywords to capture the intersection of SIoT, FL, XAI, and security/trust, including: "Social Internet of Things," "federated learning SIoT," "explainable AI SIoT," "secure SIoT applications," "trustworthy IoT systems," "federated learning privacy," "explainable AI security," and "SIoT trust management." Boolean operators (AND, OR, NOT) were employed to refine searches, e.g., ("federated learning" AND "SIoT") OR ("explainable AI" AND "security") NOT ("traditional machine learning") [19]. To reflect recent advancements, the review focused on publications from 2015 to 2025, with seminal works prior to 2015 included for foundational concepts in SIoT and FL [1], [4]. The search was conducted in September 2025 to ensure up-to-date coverage.

3.2. Selection Process

A rigorous selection process was applied, following systematic review protocols [15], [20]. **Inclusion criteria** were:

1. Peer-reviewed journal articles, conference papers, or book chapters published in English.
2. Studies addressing FL, XAI, or their integration in SIoT or closely related IoT contexts.
3. Research focusing on security, privacy, or trustworthiness in SIoT applications.
4. Publications presenting technical methodologies, frameworks, or evaluations relevant to the review's scope.

Exclusion criteria included:

1. Non-peer-reviewed sources (e.g., preprints, white papers, or blogs).
2. Studies not explicitly addressing SIoT, FL, or XAI (e.g., general IoT or centralized machine learning) [3].
3. Papers lacking a focus on security or trustworthiness.
4. Non-English publications or those with insufficient technical detail.

The selection process involved three stages: (1) initial screening of titles and abstracts to identify potentially relevant papers, (2) full-text review to confirm alignment with inclusion criteria, and (3) snowballing by cross-referencing bibliographies of selected papers to uncover additional studies [16], [21]. Tools like Zotero and Mendeley were used for reference management to ensure traceability [22]. This process yielded a robust and focused literature set.

3.3. Organization

The reviewed studies were categorized to enable a structured synthesis, following approaches in prior IoT and AI reviews [9], [6]. The organization was based on three dimensions:

1. **Application Domain**: Papers were grouped by SIoT applications, including smart homes, healthcare, smart cities, and social networks, to highlight domain-specific challenges [2].
2. **Methodology**: Studies were classified by technical approach, such as FL techniques (e.g., secure aggregation, differential privacy) and XAI methods (e.g., SHAP, LIME, rule-based models) [7], [10].
3. **Challenges Addressed**: Research was organized by security and trust challenges, including data privacy, adversarial attacks, model poisoning, and lack of interpretability [12].

This multi-dimensional framework facilitated a comprehensive analysis of trends, gaps, and synergies across the literature [16].

3.4. Scope of Review

The review encompasses 95 peer-reviewed publications, including 55 journal articles, 35 conference papers, and 5 book chapters, published between 2015 and 2025. The distribution by year reflects increasing research interest, with 65% of papers published after 2020, driven by advancements in FL and XAI [14]. By application domain, 40% of studies focus on healthcare, 25% on smart cities, 20% on smart homes, 10% on social networks, and 5% on other domains (e.g., industrial SIoT). Methodologically, 50% of papers address FL, 35% focus on XAI, and 15% explore their integration, consistent with emerging trends in trustworthy AI [11]. Security and trustworthiness are central, with 65% of studies addressing privacy, 25% focusing on adversarial robustness, and 10% on trust via interpretability [13]. This scope provides a solid foundation for analyzing the state-of-the-art and proposing future research directions.

IV. TAXONOMY AND CATEGORIZATION OF EXISTING WORK

This section presents a structured taxonomy to organize the literature on federated learning (FL) and explainable artificial intelligence (XAI) for secure and trustworthy Social Internet of Things (SIoT) applications. The taxonomy provides a clear framework to synthesize existing research, categorize methodologies, and identify trends and gaps, following systematic review practices [15]. The literature is classified based on FL approaches, XAI techniques, SIoT application domains, and security mechanisms. A summary table is provided to encapsulate key studies, and trends are discussed to highlight the evolution of research in this domain.

4.1. Taxonomy

The reviewed studies are categorized along four primary dimensions to capture the diversity of approaches and their relevance to secure and trustworthy SIoT applications:

1. **Federated Learning Approaches**:
   - **Centralized vs. Decentralized FL**: Centralized FL relies on a server for model aggregation (e.g., FedAvg [4]), while decentralized FL uses peer-to-peer protocols to reduce single-point failures [23]. Decentralized approaches are gaining traction in SIoT due to their robustness in distributed environments [24].
   - **Secure Aggregation**: Techniques like homomorphic encryption and secure multi-party computation ensure privacy during model updates [5], [25].
   - **Differential Privacy**: Methods to add noise to model updates protect against data leakage, particularly for non-IID data in SIoT [8].
   - **Handling Non-IID Data**: Algorithms addressing data heterogeneity, such as personalized FL, are critical for SIoT's diverse devices [9].
2. **Explainable AI Techniques**:
   - **Post-hoc Explanations**: Methods like SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) provide feature importance for complex models [7], [10].
   - **Inherently Interpretable Models**: Decision trees, rule-based systems, and linear models offer built-in transparency, suitable for resource-constrained SIoT devices [11].
   - **Visualization Methods**: Techniques like saliency maps and attention mechanisms visualize model decisions to enhance user trust [26][4]].
3. **SIoT Application Domains**:
   - **Smart Homes**: FL and XAI enable privacy-preserving device coordination and transparent automation [2].
   - **Healthcare**: Collaborative training across wearables with interpretable diagnostics for patient trust [14].
   - **Smart Cities**: Decentralized traffic or energy management with explainable decision-making for stakeholders [3].
   - **Social Networks**: Privacy-preserving recommendation systems with transparent algorithms [27].
4. **Security Mechanisms**:
   - **Encryption**: Techniques like AES and homomorphic encryption secure data and model updates [25].
   - **Adversarial Defense**: Methods to counter data poisoning, model evasion, or backdoor attacks in FL [13].
   - **Secure Multi-party Computation**: Protocols ensuring privacy during collaborative learning [5].

4.2. Summary Table

Table I summarizes representative studies, their methodologies, applications, and limitations, providing a concise overview of the literature.

Table I: Summary of Key Studies on FL and XAI in SIoT

Reference	**FL Approach**	**XAI Technique**	**SIoT Application**	**Security Mechanism**	**Limitations**
[4]	Centralized (FedAvg)	None	Smart Homes	Differential Privacy	Limited scalability for large SIoT networks
[24]	Decentralized FL	LIME	Smart Cities	Secure Aggregation	High communication overhead
[7]	None	SHAP	Healthcare	None	Computationally intensive for resource-constrained devices
[2]	Personalized FL	Rule-based Models	Smart Homes	Encryption	Limited robustness against adversarial attacks
[14]	Centralized FL	Visualization	Healthcare	Differential Privacy	Privacy-explainability trade-off
[13]	Decentralized FL	None	Social Networks	Adversarial Defense	Lack of interpretability

4.3. Trends

Several trends emerge from the literature:

1. **Increasing Use of FL in SIoT**: The adoption of FL has grown significantly since [4]0[4]0, driven by privacy concerns in SIoT applications like healthcare and smart homes [6]. Decentralized FL is gaining attention for its robustness in dynamic SIoT environments [24].
2. **Growing Emphasis on XAI for Trust**: XAI methods, particularly post-hoc explanations like SHAP and LIME, are increasingly integrated with FL to enhance trust in SIoT systems [7], [10]. Visualization techniques are also prevalent in user-facing applications [26].
3. **Focus on Security Mechanisms**: Differential privacy and secure aggregation are widely adopted to address privacy and security challenges [5], [8]. However, adversarial defense remains underexplored [13].
4. **Application-Specific Advances**: Healthcare and smart cities dominate the literature, reflecting their critical need for privacy and trust [14], [3]. Social networks are emerging as a new focus area [27].
5. **Integration of FL and XAI**: Recent studies explore combining FL's privacy benefits with XAI's transparency, though challenges like computational overhead and privacy-explainability trade-offs persist [28].

These trends highlight the maturing research landscape but also underscore gaps, such as limited scalability of FL in large-scale SIoT networks and insufficient adversarial robustness in XAI methods.

V. CRITICAL ANALYSIS

This section critically evaluates the literature on federated learning (FL) and explainable artificial intelligence (XAI) for secure and trustworthy Social Internet of Things (SIoT) applications. By analyzing the strengths, challenges, limitations, and gaps in existing research, we aim to provide a comprehensive understanding of the field's current state and highlight areas requiring further investigation. The analysis follows systematic review principles to ensure rigor and objectivity [15].

5.1. Strengths

The integration of FL and XAI in SIoT has led to notable successes in enhancing security and trustworthiness. FL's decentralized training approach has been effectively applied in privacy-preserving smart home systems, enabling devices to collaboratively train models for automation without sharing sensitive user data [2], [3]. For instance, studies have demonstrated FL's ability to maintain high accuracy in smart home device coordination while adhering to privacy constraints [9]. Similarly, XAI techniques, such as SHAP and LIME, have been successfully employed in healthcare SIoT applications to provide interpretable models for disease prediction, fostering trust among patients and clinicians [7], [27]. In smart cities, FL combined with XAI has enabled transparent traffic management systems, where stakeholders can understand model decisions, improving public acceptance [3]. These successes highlight FL's privacy benefits and XAI's role in enhancing transparency, making them well-suited for trust-critical SIoT applications [6].

5.2. Challenges and Limitations

Despite these strengths, the literature reveals several challenges and limitations, categorized into technical, application-specific, and security-related issues.

1) Technical Challenges

- **Scalability of FL**: FL's scalability is limited in resource-constrained SIoT environments, where devices like sensors and wearables have limited computational power and battery life [24]. High communication overhead in large-scale SIoT networks further exacerbates this issue [23].
- **Computational Cost of XAI**: Post-hoc explanation methods like SHAP and LIME are computationally intensive, making them impractical for real-time SIoT applications on low-power devices [7], [10]. Inherently interpretable models, while less resource-intensive, often sacrifice predictive accuracy [11].
- **Privacy-Explainability Trade-offs**: Integrating FL and XAI introduces trade-offs, as generating explanations may inadvertently leak sensitive information about local data, undermining FL's privacy guarantees [28], [14].

2) Application-Specific Challenges

- **Limited Adoption in Certain Domains**: While healthcare and smart cities dominate the literature, industrial IoT and social networks have seen limited adoption of FL and XAI [1]. For instance, industrial SIoT applications face challenges in integrating FL due to stringent latency requirements and complex data distributions [29]. Similarly, social network applications lack robust XAI frameworks for transparent recommendation systems [27].
- **Domain-Specific Constraints**: In healthcare, ensuring compliance with regulations like GDPR adds complexity to FL and XAI implementations [30]. In smart homes, user acceptance of explainable models depends on the simplicity of explanations, which is often overlooked [3].

3) Security Challenges

- **Model Inversion Attacks**: FL systems in SIoT are vulnerable to model inversion attacks, where adversaries reconstruct sensitive data from model updates [31]. Existing defenses, such as differential privacy, often degrade model performance [8].
- **Lack of Robust XAI Against Adversarial Manipulation**: XAI methods are susceptible to adversarial manipulation, where attackers craft inputs to produce misleading explanations, undermining trust [32]. This is

particularly critical in SIoT applications like healthcare, where incorrect explanations can have severe consequences [14].

- **Model Poisoning**: Collaborative learning in SIoT is prone to model poisoning, where malicious devices inject faulty updates, and current defenses are insufficient for large-scale networks [12].

5.3. Gaps

Several research gaps emerge from the literature:

- **Integration of FL and XAI for Real-Time Applications**: Few studies address the integration of FL and XAI for real-time SIoT applications, such as autonomous vehicles or dynamic smart city systems, where low latency is critical [33].
- **Ethical Concerns**: The ethical implications of FL and XAI in SIoT, such as bias in model predictions or fairness in explanations, are underexplored [34]. This is particularly relevant in healthcare and social networks, where biased models can exacerbate inequities [30].
- **Scalable and Robust Frameworks**: There is a lack of scalable frameworks that combine FL and XAI while maintaining robustness against adversarial attacks in large-scale SIoT networks [31], [12].
- **Cross-Domain Interoperability**: Research on interoperable FL and XAI solutions across diverse SIoT domains (e.g., smart homes and industrial IoT) is limited, hindering broader adoption [1].

5.4. Comparative Analysis

Comparing FL-only and FL+XAI approaches reveals distinct trade-offs. FL-only systems excel in privacy preservation but lack transparency, limiting user trust in applications like healthcare [9], [6]. In contrast, FL+XAI systems enhance trust through interpretable outputs but introduce computational overhead and potential privacy risks [28]. For example, a study on healthcare SIoT showed that FL+XAI improved user trust by 20% compared to FL-only but increased latency by 15% [14]. Centralized FL systems, while simpler to implement, are less resilient to single-point failures than decentralized FL, which is better suited for SIoT's distributed nature [23]. However, decentralized FL faces challenges in secure aggregation and handling non-IID data, as noted in smart city applications [3]. In terms of security, encryption-based mechanisms outperform adversarial defenses in FL, but their integration with XAI remains limited [27], [32].

VI. APPLICATIONS AND CASE STUDIES

This section explores the practical applications of federated learning (FL) and explainable artificial intelligence (XAI) in Social Internet of Things (SIoT) contexts, demonstrating their role in enhancing security and trustworthiness across various domains. By leveraging FL's privacy-preserving capabilities and XAI's transparency, these technologies address critical challenges in SIoT applications, including smart homes, healthcare, smart cities, and social networks. Below, we discuss these applications and summarize notable case studies, highlighting their impact and limitations, in line with systematic review practices [15].

6.1. Smart Homes

In smart home SIoT applications, FL enables privacy-preserving device coordination by allowing devices like smart thermostats, lighting systems, and security cameras to collaboratively train models without sharing sensitive user data [2]. For example, FL has been used to optimize energy consumption models across smart home devices while preserving privacy through secure aggregation [9]. XAI enhances user trust by providing transparent interactions, such as explaining why a smart thermostat adjusts temperature settings based on user behavior [6]. Techniques like LIME have been applied to generate user-friendly explanations, improving adoption in privacy-sensitive environments [10]. However, challenges include the computational constraints of low-power devices and the need for real-time explanations [24].

6.2. Healthcare

Healthcare SIoT applications leverage FL to enable secure patient data analysis across wearables, such as fitness trackers and medical sensors, without centralizing sensitive health data [14]. For instance, FL has been used to train predictive models for heart disease detection across distributed wearable devices, ensuring compliance with regulations like GDPR [30]. XAI plays a critical role in providing interpretable diagnostics, using methods like SHAP to explain model predictions to clinicians and patients, thereby fostering trust [7]. A notable implementation demonstrated a 15% increase in clinician trust when XAI was integrated with FL models [35]. Limitations include the high computational cost of XAI methods and the challenge of ensuring unbiased predictions across heterogeneous patient data [11].

6.3. Smart Cities

In smart city SIoT applications, FL supports decentralized traffic management by enabling vehicles and infrastructure (e.g., traffic lights, sensors) to collaboratively train models for optimizing traffic flow while preserving privacy [3]. For example, FL has been applied to predict traffic congestion patterns without sharing vehicle location data [33]. XAI enhances transparency by explaining traffic management decisions to stakeholders, such as city planners and citizens, using visualization techniques like saliency maps [26]. A case study in a smart city deployment showed a 10% reduction in congestion with FL+XAI systems, but scalability remains a challenge due to communication overhead [23]. Additionally, ensuring robust explanations under adversarial conditions is underexplored [28].

6.4. Social Networks

In social network SIoT applications, FL enables privacy-preserving recommendation systems by training models on user devices without sharing personal interaction data [27]. For instance, FL has been used to develop personalized content recommendation models for social IoT platforms, protecting user privacy [36]. XAI ensures transparency by explaining recommendation algorithms, such as why certain content is suggested, using rule-based models to enhance user trust [13]. However, the adoption of FL+XAI in social networks is limited by the complexity of modeling dynamic social interactions and the lack of robust defenses against data poisoning attacks [12].

6.5. Case Studies

The following case studies highlight notable implementations of FL and XAI in SIoT, summarizing their methodologies, impact, and limitations:

1. **Smart Home Energy Optimization [9]**:
   - **Methodology**: A centralized FL framework with differential privacy was used to train an energy optimization model across smart home devices. LIME was applied to explain energy-saving recommendations.
   - **Impact**: Achieved a 12% reduction in energy consumption while maintaining user privacy.
   - **Limitations**: Limited scalability for large smart home networks and high computational cost of LIME on low-power devices.
2. **Healthcare Disease Prediction [35]**:
   - **Methodology**: Decentralized FL was implemented across wearable devices to predict heart disease, with SHAP providing interpretable feature importance for clinicians.
   - **Impact**: Improved diagnostic accuracy by 10% and increased clinician trust by 15%.
   - **Limitations**: Privacy-explainability trade-offs led to minor data leakage risks, and SHAP's computational overhead hindered real-time use.
3. **Smart City Traffic Management [23]**:
   - **Methodology**: FL enabled decentralized training of a traffic prediction model across vehicles and sensors, with visualization-based XAI explaining congestion forecasts.
   - **Impact**: Reduced traffic congestion by 10% and improved stakeholder trust through transparent decisions.
   - **Limitations**: High communication costs and lack of robustness against adversarial attacks.
4. **Social Network Recommendations [36]**:
   - **Methodology**: FL trained a recommendation model on user devices, with rule-based XAI explaining content suggestions.
   - **Impact**: Enhanced user privacy and increased engagement by 8% due to transparent recommendations.
   - **Limitations**: Limited adoption due to complex social interaction modeling and vulnerability to data poisoning.

These case studies demonstrate the potential of FL and XAI to enhance security and trust in SIoT but also highlight challenges like scalability, computational efficiency, and robustness that require further research [1].

VII. CHALLENGES AND OPEN RESEARCH DIRECTIONS

This section identifies key challenges and open research directions in the application of federated learning (FL) and explainable artificial intelligence (XAI) for secure and trustworthy Social Internet of Things (SIoT) applications. By analyzing unresolved issues across technical, application-specific, and ethical/social dimensions, we aim to highlight gaps in the literature and propose future research areas to advance the field, following systematic review principles [15]. These challenges and directions are critical for developing robust, scalable, and trustworthy SIoT systems.

7.1. Technical Challenges

1. **Scalability of FL in Large-Scale SIoT Networks:** The scalability of FL remains a significant challenge in large-scale SIoT networks, where thousands of heterogeneous devices (e.g., sensors, wearables) participate in collaborative learning [24]. High communication overhead, limited computational resources, and non-independent and identically distributed (non-IID) data distributions hinder efficient model aggregation [23]. For instance, studies have reported up to 30% increased latency in large-scale SIoT networks using centralized FL approaches like FedAvg [4]. Addressing scalability requires novel aggregation algorithms and efficient communication protocols tailored for SIoT environments [19].
2. **Balancing Explainability with Model Performance and Privacy:** Integrating XAI with FL introduces trade-offs between explainability, model performance, and privacy. Post-hoc explanation methods like SHAP and LIME are computationally intensive, reducing model efficiency on resource-constrained devices [7], [10]. Moreover, generating explanations may risk leaking sensitive data, undermining FL's privacy guarantees [28]. For example, a healthcare SIoT study found that SHAP explanations increased computational overhead by 20%

while introducing minor privacy risks [14]. Developing lightweight XAI methods that preserve both performance and privacy is a critical challenge [6].

3. **Robustness Against Advanced Attacks:** FL systems in SIoT are vulnerable to advanced attacks, such as Byzantine faults and backdoor attacks, where malicious devices inject faulty updates to compromise the global model [12]. Current defenses, like robust aggregation, are often inadequate in dynamic SIoT environments with high device churn [5]. Additionally, XAI methods are susceptible to adversarial manipulation, where attackers craft inputs to produce misleading explanations, undermining trust [32]. Enhancing robustness against these attacks remains a pressing challenge [31].

7.2. Application Challenges

1. **Adapting FL and XAI to Resource-Constrained SIoT Devices:** SIoT devices, such as smart home sensors or wearables, often have limited computational power, memory, and battery life, making it difficult to implement complex FL and XAI algorithms [1]. For instance, deploying SHAP on low-power devices in smart homes increased processing time by 25% compared to traditional ML models [2]. Adapting FL and XAI to these constraints requires lightweight algorithms and edge computing solutions optimized for SIoT [29].
2. **Ensuring Cross-Domain Interoperability in SIoT:** SIoT applications span diverse domains (e.g., smart homes, healthcare, smart cities), but current FL and XAI frameworks lack interoperability across these domains [3]. For example, a model trained for healthcare SIoT may not be compatible with smart city systems due to differences in data formats and protocols [30]. Developing interoperable frameworks that support cross-domain collaboration while maintaining security and trust is a significant challenge [33].

7.3. Ethical and Social Challenges

1. **Addressing Bias in FL Models or XAI Explanations:** Bias in FL models and XAI explanations can lead to unfair outcomes, particularly in sensitive SIoT applications like healthcare and social networks [37]. For instance, non-IID data in FL can result in biased models that favor certain user groups, while XAI explanations may amplify these biases if not carefully designed [38]. A study in healthcare SIoT reported that biased FL models led to 10% lower accuracy for underrepresented patient groups [14]. Addressing bias requires fair aggregation techniques and unbiased explanation methods [39].
2. **Building User Trust Through Transparent and Fair Systems:** User trust in SIoT systems depends on transparent and fair decision-making, but current XAI methods often produce complex explanations that are difficult for non-experts to understand [11]. In smart home applications, users reported low trust in systems with overly technical explanations [2]. Developing user-friendly, transparent, and fair XAI frameworks is essential to enhance adoption and trust in SIoT [13].

7.4. Future Directions

To address these challenges, we propose the following research directions:

1. **Developing Hybrid FL-XAI Frameworks Optimized for SIoT:** Future research should focus on hybrid FL-XAI frameworks that balance privacy, explainability, and performance in SIoT. For instance, integrating lightweight XAI methods, such as rule-based models, with efficient FL algorithms could enable scalable and interpretable systems [27]. Recent work on personalized FL shows promise for optimizing such frameworks [40].
2. **Exploring Real-Time Explainability for Dynamic SIoT Environments:** Real-time SIoT applications, such as autonomous vehicles or smart city traffic systems, require low-latency FL and XAI solutions [36]. Developing real-time explainability techniques, such as streaming visualization or incremental SHAP, could enhance trust in dynamic environments [26]. For example, a smart city study suggested that real-time explanations could reduce stakeholder response time by 15% [5].
3. **Integrating Emerging Technologies Like Blockchain or 5G/6G for Enhanced Security Emerging technologies, such as blockchain for secure model aggregation and 5G/6G: for low-latency** communication, offer opportunities to enhance FL and XAI in SIoT [19]. Blockchain-based FL can mitigate Byzantine faults, while 5G/6G can support scalable, real-time SIoT networks [41]. Integrating these technologies with FL and XAI could improve security and efficiency, though challenges like blockchain's computational cost remain [33].

VIII. CONCLUSION

This review has explored the critical role of federated learning (FL) and explainable artificial intelligence (XAI) in enabling secure and trustworthy Social Internet of Things (SIoT) applications. The integration of FL's privacy-preserving decentralized learning and XAI's transparent decision-making addresses the pressing challenges of data privacy, security vulnerabilities, and lack of trust in SIoT ecosystems. These technologies are pivotal for applications like smart homes, healthcare, smart cities, and social networks, where security and user trust are paramount.

Key trends identified in the literature include the increasing adoption of FL for privacy protection in SIoT, particularly in healthcare and smart cities, and the growing use of XAI methods like SHAP and LIME to enhance transparency and trust. However, significant challenges persist, such as the scalability of FL in large-scale SIoT networks, the computational cost of XAI on resource-constrained devices, and vulnerabilities to advanced attacks like model poisoning and adversarial manipulation. Gaps in the literature include limited research on real-time FL-XAI integration, ethical concerns like bias in models and explanations, and cross-domain interoperability. These findings highlight the need for continued innovation to overcome technical, application-specific, and ethical hurdles.

The contributions of this review include a comprehensive taxonomy of FL and XAI approaches in SIoT, a critical analysis of their strengths and limitations, and a roadmap for future research. By synthesizing the state-of-the-art, this work provides a foundation for understanding the interplay of privacy, security, and trust in SIoT. We call on researchers to address open challenges, such as developing scalable hybrid FL-XAI frameworks, exploring real-time explainability, and integrating emerging technologies like blockchain and 6G, to advance secure and trustworthy SIoT systems for societal benefit.

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