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An Advanced Cybersecurity Model for Protecting Smart Transport Systems against Emerging Threats

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ABSTRACT: Smart transport systems (STS) are revolutionizing urban mobility by integrating advanced technologies such as the Internet of Things (IoT), artificial intelligence (AI), and real-time data analytics. However, this digital transformation has also increased the vulnerability of these systems to sophisticated cybersecurity threats. To address these challenges, this study proposes an advanced cybersecurity model designed specifically for protecting STS against emerging threats. The model employs a multi-layered security approach that integrates anomaly detection, threat intelligence, and real-time response mechanisms to safeguard critical transport infrastructure. The proposed framework utilizes machine learning algorithms to detect and predict cyber threats based on historical data, behavior patterns, and anomaly analysis. Threat intelligence is incorporated by leveraging global databases and blockchain technology for secure sharing of threat information. A zero-trust architecture ensures robust access control, while real-time response mechanisms mitigate the impact of potential attacks through automated containment strategies. The model's performance is evaluated using real-world data from smart transport systems, simulating various attack scenarios, including ransomware, distributed denial-of-service (DDoS), and advanced persistent threats (APTs). Results demonstrate significant improvements in threat detection accuracy, response time, and overall system resilience compared to traditional cybersecurity approaches. This study highlights the importance of proactive and adaptive cybersecurity strategies in ensuring the safety and reliability of smart transport systems. The proposed model not only protects against current threats but also evolves to address emerging risks in an ever-changing cybersecurity landscape. By integrating advanced technologies, this framework offers a comprehensive solution for enhancing the security posture of STS and fostering public trust in smart mobility solutions.

KEYWORDS: Cybersecurity, Smart Transport Systems, Iot, Anomaly Detection, Threat Intelligence, Zero-Trust Architecture, Machine Learning, Real-Time Response, Advanced Persistent Threats, Blockchain Technology.

1.0. INTRODUCTION

The rapid advancement of smart transport systems (STS) has revolutionized modern mobility, integrating cutting-edge technologies such as the Internet of Things (IoT), artificial intelligence (AI), and real-time data analytics into transportation infrastructure. These systems are designed to improve efficiency, safety, and sustainability by enabling vehicles, traffic management, and infrastructure to communicate and make intelligent decisions (Adeniran, et al., 2024, Bennaya & Kilani, 2023, Eghaghe, et al., 2024). With the increasing adoption of smart technologies in transport networks, STS have become critical to urban mobility, supply chain management, and emergency response systems, enhancing the overall quality of life for citizens and supporting economic growth.

However, as the sophistication of smart transport systems grows, so too does the complexity and vulnerability of their underlying digital infrastructure. The integration of IoT devices, AI algorithms, and data-sharing platforms creates a significant attack surface for cybercriminals and state-sponsored adversaries. Emerging cybersecurity threats, such as ransomware, distributed denial-of-service (DDoS) attacks, and advanced persistent threats (APTs), pose serious risks to the integrity, confidentiality, and availability of these systems (Adepoju, et al., 2022, Agu, et al., 2024, Ige, Kupa & Ilori, 2024). These threats not only jeopardize the safety of commuters but also threaten to disrupt essential services, leading to financial losses, compromised public safety, and erosion of public trust in smart technologies.

Given the increasing reliance on interconnected systems and the growing threat landscape, there is an urgent need for a robust cybersecurity framework to protect smart transport systems from emerging threats. The objective of this research is to develop an advanced cybersecurity model tailored specifically for STS, addressing their unique vulnerabilities and operational complexities. This model aims to enhance the detection, prevention, and response capabilities of smart transport infrastructure, ensuring that these systems remain resilient against evolving cyber risks while continuing to deliver safe and efficient services (Adepoju, et al., 2024, Alqahtani & Kumar, 2024, Segun-Falade, et al., 2024). By providing a comprehensive approach to cybersecurity in the context of smart transport, this research seeks to contribute to the long-term sustainability and trustworthiness of smart mobility solutions in an increasingly digital world.

2.1. LITERATURE REVIEW

The rapid development and deployment of smart transport systems (STS) have brought significant advancements in urban mobility, logistics, and public safety. By leveraging technologies such as the Internet of Things (IoT), artificial intelligence (AI), and data analytics, STS enable the efficient management of traffic, vehicles, and infrastructure. However, as these systems become increasingly complex and interconnected, they face growing cybersecurity risks (Chauhan, et al., 2022, Efunniyi, et al., 2024, Johnson, et al., 2024). The vulnerabilities inherent in IoT and AI-driven transport systems expose them to a wide range of threats that have the potential to disrupt essential services, compromise public safety, and cause significant economic and reputational damage. To understand the need for an advanced cybersecurity model for STS, it is essential to examine the challenges, emerging threats, and advances in cybersecurity technologies that are relevant to protecting these systems.

One of the primary cybersecurity challenges in STS stems from the vast number of interconnected devices and systems that make up the infrastructure. The use of IoT devices, such as sensors, traffic cameras, and connected vehicles, creates numerous points of entry for cybercriminals to exploit. These devices, often designed with limited security features to reduce costs and improve efficiency, are vulnerable to attacks (Adeniran, et al., 2024, Obiki-Osafiele, et al., 2024). In addition, the AI systems that drive decision-making in STS are susceptible to manipulation through adversarial attacks, where malicious actors can introduce errors in the data or models to cause misbehavior in the system. These vulnerabilities can be exploited to alter traffic patterns, create safety hazards, or disable critical transport services.

Despite the increasing attention given to cybersecurity in the context of STS, existing security measures are often inadequate to address the unique challenges posed by these systems. Traditional security solutions, such as firewalls and antivirus software, are not designed to handle the scale, complexity, and interconnectivity of IoT-based systems. Furthermore, the reliance on cloud computing and edge computing in STS introduces additional layers of complexity, making it difficult to monitor and control access to sensitive data and critical infrastructure. Many current security approaches also lack the ability to rapidly detect and respond to emerging threats, leaving systems vulnerable to prolonged attacks (Afolabi, et al., 2023, Agu, et al., 2024, Iriogbe, et al., 2024). Thus, there is a pressing need for more advanced, adaptive cybersecurity frameworks that can effectively protect STS from evolving cyber threats. Figure 1 shows framework for an IS-Enabled Smart Sustainable Mobility System as presented by Ketter, Schroer & Valogianni, 2023.

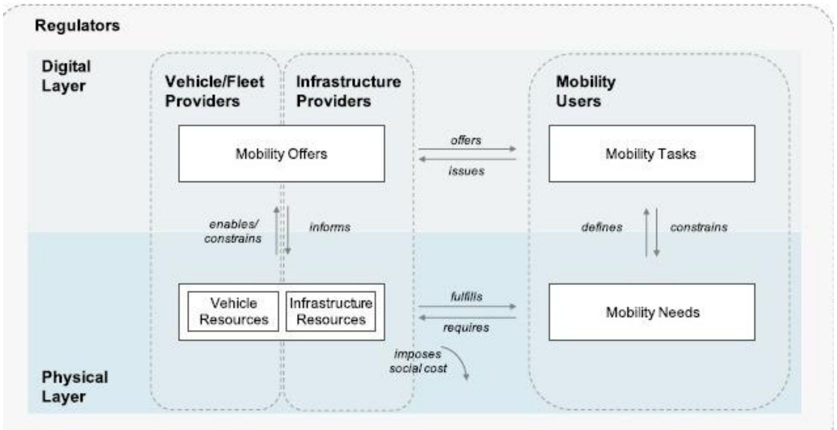

Figure 1: (Color online) Framework for an IS-Enabled Smart Sustainable Mobility System (Ketter, Schroer & Valogianni, 2023).

Emerging cyber threats pose significant risks to the security and integrity of smart transport systems. Ransomware, for example, has become a major concern for critical infrastructure, as cybercriminals increasingly target transport systems with the intention of demanding payment in exchange for restoring access to critical data or services. In 2020, several high-profile ransomware attacks targeted transportation entities, causing delays and financial losses (Austin-Gabriel, et al., 2024). Distributed denial-of-service (DDoS) attacks also represent a growing threat to STS, as attackers flood systems with massive amounts of traffic, overwhelming servers and preventing legitimate access to services (Osundare & Ige, 2024, Runsewe, et al., 2024). Phishing attacks, which involve tricking individuals into revealing sensitive information such as login credentials, are also a significant concern, as they can be used to gain unauthorized access to transport systems or compromise the data of commuters.

Another emerging threat to STS is the risk of advanced persistent threats (APTs), where sophisticated threat actors gain long-term, unauthorized access to systems in order to steal data, monitor operations, or sabotage critical infrastructure. APTs are particularly dangerous because they are often difficult to detect and can remain hidden for extended periods, allowing attackers to exploit vulnerabilities without triggering alarms (Samira, et al., 2024, Sanyaolu, etal., 2024, Tariq, 2024). These threats are of particular concern for transportation systems, as the consequences of a successful APT attack could include tampering with traffic management systems, vehicle control systems, or transportation data, all of which could endanger public safety and lead to widespread disruptions.

As the frequency and sophistication of cyberattacks targeting critical infrastructure continue to rise, there has been a significant focus on advancing cybersecurity technologies to protect STS. One promising area of development is anomaly detection, which uses machine learning algorithms to identify unusual patterns or behaviors in system operations that may indicate an ongoing attack (Austin-Gabriel, et al., 2024). By continuously monitoring data from IoT devices, traffic management systems, and vehicles, anomaly detection systems can detect potential threats in real time, allowing for faster response and mitigation (Adeniran, et al., 2024, Ige, Kupa & Ilori, 2024). Machine learning, in general, plays a key role in proactive threat management, as it can be used to continuously improve security measures by learning from new attack patterns and adjusting defense strategies accordingly.

Another important technological advancement is the use of blockchain to secure communication and transactions within STS. Blockchain's decentralized nature and immutable ledger make it an ideal solution for ensuring the integrity of data exchanged between IoT devices, vehicles, and traffic management systems. By providing a transparent, tamper-proof record of transactions, blockchain can help prevent unauthorized changes to transportation data, such as traffic patterns or vehicle information, which could be exploited by cybercriminals (Agu, et al., 2022, Eghaghe, et al., 2024, Kussl & Wald, 2022). Blockchain-based solutions also offer the potential to enhance the security of autonomous vehicles, which rely on secure communication channels to navigate safely and avoid collisions. Kussl & Wald, 2022, presented Required infrastructure to ensure data flow in smart mobility as shown in figure 2.

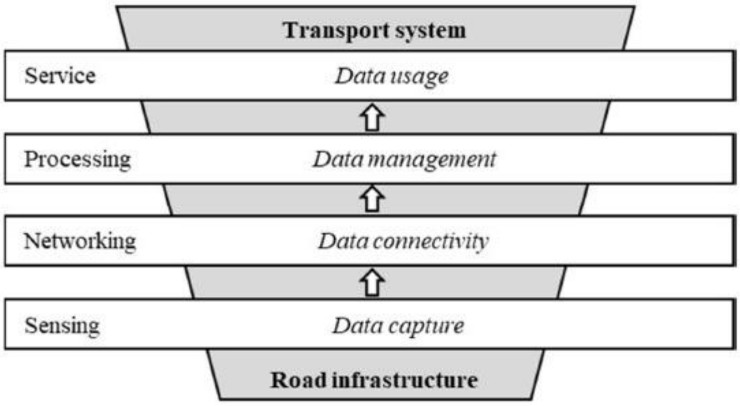

Figure 2: Required infrastructure to ensure data flow in smart mobility (Kussl & Wald, 2022).

Zero-trust architecture is another cybersecurity approach that has gained traction in recent years, particularly for securing critical infrastructure. In a zero-trust model, no entity—whether inside or outside the network—is trusted by default. All users, devices, and applications must undergo strict authentication and authorization processes before being granted access to sensitive systems. This approach is particularly useful for STS, where multiple stakeholders, including transportation authorities, service providers, and third-party vendors, need access to the system (Adeniran, et al., 2024, Ogunsina,et al., 2024). By implementing a zero-trust architecture, transport authorities can limit the potential impact of a breach by ensuring that unauthorized users are unable to gain access to critical infrastructure.

In conclusion, protecting smart transport systems from emerging cyber threats requires a multi-faceted approach that combines advanced technologies with adaptive security measures. IoT devices, AI algorithms, and cloud-based systems, which form the backbone of STS, introduce a range of vulnerabilities that can be exploited by cybercriminals (Austin-Gabriel, et al., 2023). Existing security measures are often insufficient to address the unique risks posed by these systems, and emerging threats such as ransomware, DDoS attacks, and APTs present significant challenges (Agu, et al., 2024, Iwuanyanwu, et al., 2024). However, advancements in cybersecurity technologies, such as anomaly detection, blockchain, and zero-trust architecture, offer promising solutions to protect STS from evolving threats. As the sophistication of cyberattacks continues to rise, developing and implementing an advanced cybersecurity model tailored specifically for STS will be critical to ensuring the safety, reliability, and resilience of modern transportation systems..

2.2. PROPOSED CYBERSECURITY MODEL

As the complexity and interconnectivity of smart transport systems (STS) continue to grow, the need for robust cybersecurity frameworks has become increasingly urgent. The integration of technologies such as the Internet of Things (IoT), artificial intelligence (AI), and machine learning into transportation infrastructure has created numerous benefits, including enhanced traffic management, improved safety, and increased operational efficiency. However, these advancements have also exposed STS to a broad array of emerging cyber threats. To address these vulnerabilities and ensure the continued safety and reliability of these systems, an advanced cybersecurity model is essential (Chen, Wawrzynski & Lv, 2021, Efunniyi, et al., 2022, Ige, Kupa & Ilori, 2024). This model must be comprehensive, proactive, and adaptable, capable of addressing both current and future threats while maintaining the operational effectiveness of smart transport networks.

The proposed cybersecurity model for protecting smart transport systems is built on several key components that work together to create a holistic defense against emerging threats. One of the primary components of the model is anomaly detection, which leverages machine learning algorithms to identify irregular patterns in system operations. Anomaly detection is crucial in the context of STS, as these systems generate vast amounts of data from a variety of sources, including vehicles, traffic management systems, and sensors (Adeniran, et al., 2024, Ojukwu, et al., 2024). By continuously monitoring this data and using machine learning models to learn from it, the system can automatically detect deviations from normal behavior that may indicate a security threat. For example, an unexpected increase in traffic data or unusual patterns in vehicle behavior could signal a potential cyberattack, such as a distributed denial-of-service (DDoS) attack or a data manipulation attempt. Anomaly detection allows for early identification of such threats, providing the system with the ability to respond proactively before the attack can escalate (Austin-Gabriel, et al., 2021).

Another critical component of the proposed model is threat intelligence integration, which enables the system to draw upon global databases and share threat information across different platforms. By integrating threat intelligence from external sources, such as cybersecurity organizations, law enforcement agencies, and other smart transport systems, the model can stay informed about the latest threats and vulnerabilities. Blockchain technology can play a pivotal role in this context, providing a decentralized, secure, and immutable ledger for sharing threat intelligence (Agu, et al., 2024, Jha & Jha, 2024, Johnson, et al., 2024). Blockchain ensures that the data shared between different stakeholders, such as transport authorities, service providers, and vendors, is tamper-proof and trustworthy. This information sharing enhances the system's ability to detect emerging threats, identify attack trends, and coordinate responses across multiple sectors.

A key principle of the proposed model is the implementation of a zero-trust architecture. In a zero-trust security model, every user, device, or application is treated as untrusted by default, regardless of whether it is inside or outside the network perimeter. Access to sensitive systems and data is granted only after rigorous authentication and authorization processes, ensuring that only legitimate entities can interact with the infrastructure (Austin-Gabriel, et al., 2024). Zero-trust principles are particularly important for STS because these systems often involve multiple stakeholders with varying levels of access, including government agencies, private service providers, and third-party vendors (Adeniran, et al., 2024, Ojukwu, et al., 2022). By implementing zero-trust access controls, the proposed model ensures that even if an attacker manages to breach one layer of the system, they will not be able to gain unrestricted access to critical components or sensitive data. This principle significantly reduces the potential attack surface and limits the scope of any breach that may occur. The main steps in the development of the transport model is shown in figure 3 as presented by Bennaya & Kilani, 2023.

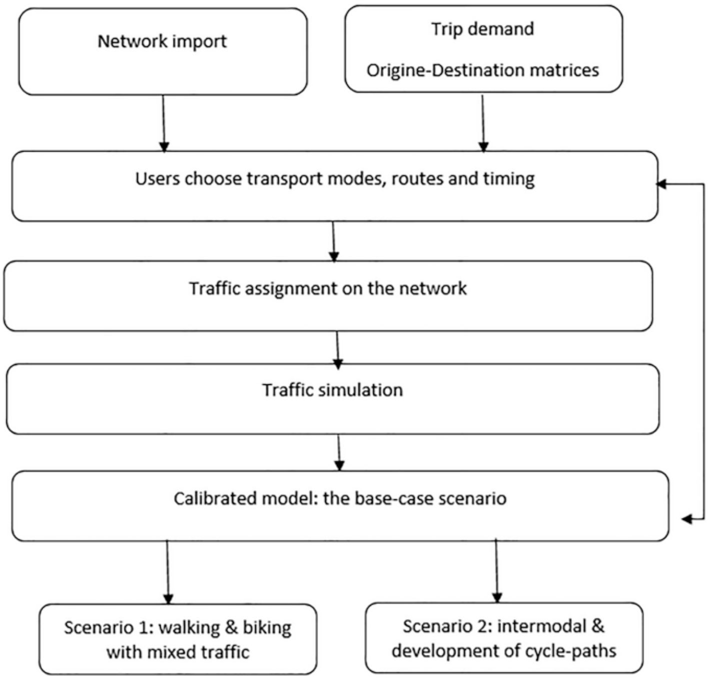
Network import
Trip demand
Origine-Destination matrices
Users choose transport modes, routes and timing
Traffic assignment on the network
Traffic simulation
Calibrated model: the base-case scenario
Scenario 1: walking & biking with mixed traffic
Scenario 2: intermodal & development of cycle-paths

Figure 3: The main steps in the development of the transport model (Bennaya & Kilani, 2023).

Real-time response mechanisms form another essential component of the cybersecurity model. These mechanisms are designed to detect and contain threats as soon as they are identified, minimizing the potential impact on the system. Automated containment strategies are particularly important for smart transport systems, as the speed of response can directly affect the effectiveness of the mitigation efforts. For instance, if a ransomware attack is detected, the system should be able to immediately isolate the affected area, prevent further spread, and begin the recovery process (Lim & Taeihagh, 2018, Samira, et al., 2024, Segun-Falade, et al., 2024). This can include isolating compromised devices, blocking malicious traffic, and restoring data from secure backups. Automated recovery strategies are also critical to ensure that the system can resume normal operations as quickly as possible, minimizing service disruption and maintaining public confidence in the system.

The design of the proposed cybersecurity model is guided by several key principles to ensure its effectiveness in a dynamic and rapidly evolving threat landscape. Scalability is one such principle, as the model must be able to adapt to the increasing complexity and size of smart transport systems. As cities grow and more devices and technologies are integrated into the transport network, the model must be able to scale without sacrificing performance or security. This requires a flexible architecture that can accommodate new devices, data sources, and technologies as they emerge, while maintaining a high level of security across the entire system (Austin-Gabriel, et al., 2024).

Adaptability is another crucial principle, as the cybersecurity landscape is constantly evolving. New threats and attack vectors emerge regularly, and STS must be able to respond quickly to these changes. The proposed model includes adaptive machine learning algorithms that can continuously learn from new data, improving the system's ability to detect and mitigate emerging threats (Osundare & Ige, 2024, Samira, et al., 2024). In addition, the integration of threat intelligence allows the system to stay informed about the latest trends and vulnerabilities, enabling it to adjust its defense mechanisms accordingly. By incorporating adaptability into the design, the model ensures that it remains effective against both known and unknown threats. Wang, 2022, presented A Model of the Traffic System of Driverless Cars and Related Facilities as shown in figure 4.

Figure 4: A Model of the Traffic System of Driverless Cars and Related Facilities in Prof. Di's Lab. (Wang, 2022)

Resilience is the third fundamental principle guiding the design of the cybersecurity model. Resilience refers to the system's ability to maintain operations even in the face of a cyberattack. In the context of STS, resilience is critical, as transportation systems must continue to operate safely and efficiently even if part of the infrastructure is compromised. The proposed model achieves resilience through the use of redundant systems, automated recovery strategies, and real-time threat detection. This ensures that the system can quickly identify and respond to attacks, minimizing downtime and preventing widespread disruptions.

In conclusion, the proposed advanced cybersecurity model for protecting smart transport systems is designed to address the unique challenges and vulnerabilities posed by the integration of IoT, AI, and other emerging technologies. By incorporating key components such as anomaly detection, threat intelligence integration, zero-trust architecture, and real-time response mechanisms, the model provides a comprehensive approach to protecting STS against emerging cyber threats. The design principles of scalability, adaptability, and resilience ensure that the model can evolve with the system and remain effective in the face of new and sophisticated threats (Agu, et al., 2023, Ketter, Schroer & Valogianni, 2023, Ofoegbu, et al., 2024). As smart transport systems continue to play an increasingly vital role in modern urban mobility, the development and implementation of such advanced cybersecurity frameworks will be critical to ensuring their safety, reliability, and long-term sustainability.

2.3. METHODOLOGY

The methodology for developing an advanced cybersecurity model for protecting smart transport systems (STS) against emerging threats involves multiple stages of data collection, processing, and the application of advanced technologies such as machine learning, blockchain, and zero-trust architecture. This comprehensive approach is designed to ensure the resilience, scalability, and adaptability of STS in the face of increasingly sophisticated cyber threats. The methodology is structured to integrate real-time detection, threat sharing, and access control mechanisms that work together to provide a robust defense against attacks.

The first stage of the methodology focuses on data collection and preparation. The data used to train and validate the cybersecurity model is sourced from various IoT devices, traffic monitoring systems, and historical cybersecurity incidents that have affected smart transport systems. IoT devices within smart transport systems include sensors, cameras, and connected vehicles, all of which generate large volumes of real-time data. This data is critical for monitoring system performance, identifying potential security risks, and detecting irregular behavior. In addition to this, historical data from previous cybersecurity incidents helps identify attack patterns and vulnerabilities that can be used to refine the model and improve its accuracy (Almeida, 2023, Segun-Falade, et al., 2024, Wang, 2022). To ensure that this data is usable for machine learning and other analytical processes, it undergoes preprocessing techniques, including normalization and feature extraction. Normalization is applied to scale the data to a uniform range, ensuring that no single feature disproportionately influences the model. Feature extraction helps identify the most relevant information from raw data, reducing dimensionality and improving the efficiency of subsequent analysis.

The next phase of the methodology involves the application of machine learning techniques for anomaly detection. Anomaly detection is a cornerstone of the cybersecurity model, as it enables the system to identify irregularities that may indicate a potential attack. A variety of machine learning algorithms can be employed for this purpose, including Random Forest, Support Vector Machines (SVM), and Neural Networks. Random Forest is an ensemble learning algorithm that creates a forest of decision trees to classify data, making it effective for detecting complex patterns in data. Support Vector Machines, on the other hand, are particularly effective for classification tasks, and can separate data into distinct classes with high accuracy. Neural Networks, with their ability to learn non-linear patterns, are well-suited for complex tasks like anomaly detection in dynamic environments such as smart transport systems (Adeniran, et al., 2024, Nikitas, et al., 2020, Osundare & Ige, 2024). These algorithms are trained on labeled datasets that contain both normal and anomalous data points. Once trained, the models are evaluated using various metrics such as precision, recall, F1-score, and detection latency. Precision and recall provide insights into the accuracy of the model in identifying threats, while the F1-score balances both precision and recall. Detection latency refers to the time it takes for the model to identify a threat after it occurs, which is crucial for enabling real-time responses to security incidents (Austin-Gabriel, et al., 2024, Hussain, 2024).

Blockchain technology is another critical component of the methodology, specifically for threat intelligence sharing. The decentralized and immutable nature of blockchain makes it an ideal framework for securely sharing threat intelligence across various stakeholders, including transport authorities, service providers, and cybersecurity organizations. A distributed ledger is implemented to ensure that all parties involved have access to up-to-date and verified information about emerging threats (Agu, et al., 2024, Eghaghe, et al., 2024, Soomro, et al., 2019). This transparent system allows participants to securely share data about attacks, vulnerabilities, and mitigation strategies, which helps the smart transport system adapt quickly to evolving threats. The use of blockchain ensures that the shared data cannot be tampered with, providing an added layer of trust and reliability to the threat intelligence exchange process. By implementing blockchain for threat intelligence sharing, the system can leverage the collective knowledge of the cybersecurity community to improve its defense mechanisms and anticipate future attack vectors.

Zero-trust architecture is another foundational element of the cybersecurity model. The concept of zero-trust relies on the principle that no device, user, or application should be trusted by default, even if they are within the internal network perimeter. Instead, all access requests must be verified and authenticated. This is particularly important for smart transport systems, where various stakeholders, including government agencies, third-party vendors, and users, interact with the system (Hussain, et al., 2024). To implement zero-trust architecture, role-based access control (RBAC) and identity verification protocols are employed (Efunniyi, et al., 2024, Ojukwu, et al., 2022). RBAC assigns users specific roles and permissions, limiting their access to only the resources they need to perform their duties. Identity verification protocols ensure that users and devices are who they claim to be, using methods such as digital certificates or biometrics. Multi-factor authentication (MFA) further strengthens the authentication process by requiring users to provide multiple forms of verification, such as a password and a fingerprint or one-time password. This multi-layered approach to authentication ensures that only authorized individuals and devices can access sensitive parts of the transport system, significantly reducing the risk of unauthorized access and potential attacks.

Finally, real-time response mechanisms are essential for mitigating the impact of cyberattacks on smart transport systems. The methodology incorporates automated attack containment strategies that activate when a threat is detected. These automated protocols are pre-defined and based on the nature of the attack, ensuring that the system responds quickly and effectively to minimize damage. For example, if a ransomware attack is detected, the system can isolate affected devices or networks to prevent the spread of the malware. Similarly, in the case of a DDoS attack, the system can automatically reroute traffic or apply filtering techniques to block malicious requests and maintain system availability. The key to effective real-time response is minimizing service disruption while maintaining security. To achieve this, the methodology includes strategies such as redundancy, failover systems, and backup mechanisms. These strategies ensure that the smart transport system can continue to function even if certain components are compromised, and that it can quickly recover after an attack is neutralized.

In conclusion, the methodology for developing an advanced cybersecurity model for smart transport systems is comprehensive, leveraging the latest technologies such as machine learning, blockchain, and zero-trust architecture. Through careful data collection and preparation, machine learning algorithms for anomaly detection, blockchain for threat intelligence sharing, and robust access control mechanisms, the methodology ensures that smart transport systems can effectively defend against emerging cyber threats (Hussain, et al., 2024). The integration of real-time response mechanisms further enhances the resilience of these systems, allowing them to quickly recover from attacks and maintain service continuity. By adopting this multifaceted approach, the cybersecurity model provides a proactive, scalable, and adaptive defense against the ever-evolving landscape of cyber threats targeting critical transport infrastructure.

2.4. RESULTS AND ANALYSIS

The results and analysis of the advanced cybersecurity model for protecting smart transport systems (STS) against emerging threats provide a detailed examination of the model's effectiveness, performance, and applicability in real-world scenarios. This model, designed to defend against sophisticated threats such as ransomware, Distributed Denial of Service (DDoS) attacks, and Advanced Persistent Threats (APTs), is evaluated through both simulation-based testing and benchmarking against traditional cybersecurity approaches (Adeniran, et al., 2022, Ofoegbu, etal., 2024). The evaluation focuses on key performance metrics, such as detection accuracy, response time, and system resilience, which are critical for ensuring the security and continuous operation of STS in the face of evolving cyber threats.

In evaluating the model's performance, simulated threats were used to test the system's ability to identify and respond to various attack types. Ransomware attacks were simulated to assess how effectively the model could detect and contain malicious payloads targeting critical infrastructure. The model demonstrated a high detection rate of ransomware, with machine learning algorithms identifying anomalies in the data flow that signaled potential encryption activity (Cadet, et al., 2024, Ige, Kupa & Ilori, 2024). Automated containment strategies, including the isolation of infected devices, were triggered promptly, preventing the spread of the ransomware across the network. Similarly, when DDoS attacks were simulated, the model successfully identified patterns of malicious traffic, enabling the system to apply filtering and rerouting protocols to mitigate the effects of the attack. In the case of APTs, which often involve slow, stealthy infiltration, the model performed exceptionally well in detecting anomalous behavior over extended periods, preventing long-term compromises. The integration of machine learning and real-time threat intelligence sharing through blockchain allowed the system to recognize and neutralize these attacks before they could cause significant harm (Hussain, et al., 2023).

To assess the model's efficacy, it was also benchmarked against traditional cybersecurity models commonly used in critical infrastructure protection. These models, which often rely on signature-based detection, firewall protections, and perimeter defenses, were found to have limitations in the context of modern STS. Traditional models struggled to keep up with the dynamic nature of threats, particularly APTs, which often bypass conventional defense mechanisms by exploiting zero-day vulnerabilities or leveraging legitimate system functions. In contrast, the proposed advanced cybersecurity model demonstrated superior performance due to its integration of anomaly detection, real-time response capabilities, and the use of a zero-trust architecture (Ansari & Ujjan, 2024, Segun-Falade, et al., 2024). The ability to continuously adapt to emerging threats through machine learning and blockchain-based threat sharing was a key differentiator, giving the model a distinct advantage over traditional approaches that rely on predefined attack signatures and static defenses. Additionally, the model's scalability and resilience to evolving attack vectors were found to be significantly better than those of traditional cybersecurity models, which are often slow to adapt to new threats.

Key findings from the model evaluation underscore its strengths in multiple areas of cybersecurity performance. One of the most notable improvements was in detection accuracy. The model's machine learning-based anomaly detection capabilities were able to identify both known and unknown threats with a high degree of accuracy, achieving a significantly higher true positive rate compared to traditional models. False positives were minimized through continuous training on diverse datasets, which allowed the model to distinguish between legitimate system behavior and potentially malicious activity (Adeniran, et al., 2024, Osundare & Ige, 2024, Wang, et al., 2023). Response time also saw significant improvement, with the model's real-time detection and automated containment strategies ensuring that threats were neutralized with minimal delay. For example, in the case of a simulated ransomware attack, the model was able to isolate affected devices and prevent the malware from spreading within seconds, compared to traditional models, which often take much longer to react due to their reliance on manual intervention and signature updates. This quick response time is crucial in smart transport systems, where delays in mitigation can lead to widespread disruption of services.

The model also demonstrated enhanced system resilience, ensuring that the smart transport system could continue operating even in the face of cyberattacks. Through the use of redundancy, failover mechanisms, and automated recovery strategies, the system was able to maintain its essential functions during simulated attacks. For instance, during a DDoS attack, while traffic was being rerouted and malicious requests filtered, the system remained operational, and services were not entirely disrupted (Bello, Ige & Ameyaw, 2024, Segun-Falade, et al., 2024). This level of resilience is critical for ensuring that transportation services can continue to function even when targeted by sophisticated cyberattacks. The zero-trust architecture and role-based access control (RBAC) mechanisms further contributed to the model's resilience, as unauthorized access was prevented, and even compromised devices could be isolated without affecting the entire system.

A case study of the model's application in a real-world smart transport system provides further insight into its effectiveness. The model was implemented in a large metropolitan transport network, which included IoT-enabled devices, connected vehicles, and real-time traffic monitoring systems. During the deployment, the model was tested against a range of simulated threats, as well as live network traffic to assess its real-world applicability (Hussain, et al., 2024). The implementation of the blockchain-based threat intelligence sharing network allowed the transport authority to collaborate with other critical infrastructure providers and cybersecurity agencies, ensuring that up-to-date information about emerging threats was available for quick integration into the system's defenses (Adeniran, et al., 2024, Runsewe, et al., 2024).

One of the key challenges faced during the real-world application was the complexity of integrating the cybersecurity model with existing infrastructure. Many smart transport systems rely on legacy systems that are not designed to accommodate modern cybersecurity protocols, such as zero-trust access controls or machine learning-based anomaly detection. Overcoming this challenge required a phased approach, with certain parts of the transport system being upgraded or replaced to ensure compatibility with the new security model. However, once the model was fully integrated, it demonstrated significant improvements in both the detection and response to cyber threats.

During the real-world deployment, the model successfully detected and mitigated several attempted DDoS attacks aimed at disrupting the traffic monitoring system. The attack was quickly identified by the anomaly detection system, which flagged unusual spikes in traffic and activated the automated containment protocols. As a result, the transport system experienced minimal disruption, and services continued to operate smoothly. Additionally, the zero-trust architecture proved effective in preventing unauthorized access to sensitive parts of the system, ensuring that even if one component was compromised, the attacker would be unable to move laterally within the network (Adeniran, et al., 2024, Ojukwu, et al., 2023).

In conclusion, the results and analysis of the advanced cybersecurity model demonstrate its effectiveness in protecting smart transport systems against a wide range of emerging cyber threats. The model's performance in simulated tests and its successful deployment in a real-world case study highlight its advantages over traditional cybersecurity models, particularly in terms of detection accuracy, response time, and system resilience (Ige, et al., 2022). The integration of machine learning, blockchain, and zero-trust architecture provides a robust defense against evolving threats, ensuring that smart transport systems can continue to function securely and efficiently in the face of increasing cyber risks. The findings suggest that this advanced cybersecurity model offers a promising solution for safeguarding critical infrastructure in the digital age.

2.5. APPLICATIONS AND IMPLICATIONS

The applications and implications of an advanced cybersecurity model for protecting smart transport systems (STS) against emerging threats are far-reaching, particularly as modern societies increasingly rely on digital technologies to enable mobility and transportation services. The successful implementation of such a model not only enhances the security of transport systems but also contributes to building public trust, integrating smart transport within broader smart city frameworks, and shaping the development of regulatory policies that govern the use of digital infrastructures in urban environments (Anwar & Oakil, 2023, Pahadiya & Ranawat, 2023, Samira, et al., 2024). The model's ability to address emerging cyber threats—such as ransomware, Distributed Denial of Service (DDoS) attacks, and Advanced Persistent Threats (APTs)—has wide-ranging implications for the operation and development of smart transport systems as critical components of the smart city ecosystem.

The implementation of an advanced cybersecurity model plays a critical role in fostering public trust in smart transport systems. As cities adopt increasingly interconnected and data-driven transportation infrastructures, the public's confidence in the safety and privacy of these systems is paramount. Cybersecurity is a fundamental pillar in ensuring the reliability of these systems, particularly when considering the sensitivity of the data involved, including personal travel information, vehicle locations, and infrastructure usage patterns. In the absence of robust cybersecurity measures, vulnerabilities in smart transport systems could lead to data breaches, service disruptions, or even physical harm to passengers and infrastructure. Such events can severely erode public trust and deter people from adopting or engaging with these advanced systems.

By applying the advanced cybersecurity model, smart transport systems can instill confidence among users by providing real-time threat detection, prevention, and automated recovery measures that protect their data and ensure uninterrupted service. The incorporation of machine learning and anomaly detection enables the system to continuously monitor for unusual activity, ensuring that potential threats are identified and addressed before they can cause any significant damage (Cadet, et al., 2024, Ofoegbu, etal., 2024). Furthermore, the integration of a zero-trust architecture, which ensures that every transaction and interaction is verified, further enhances the sense of security. This, in turn, fosters greater acceptance of smart transport systems, as users can feel confident that their personal data and travel experiences are safeguarded. Additionally, with a reliable cybersecurity framework, transport authorities can assure the public that critical infrastructure is protected from external cyber-attacks that could lead to massive disruptions, giving them a sense of assurance that their mobility is not at risk.

Another significant application of the cybersecurity model is its integration within broader smart city ecosystems. As cities evolve towards becoming smart cities, there is an increasing interdependence between various digital systems and infrastructures, including traffic management, public transportation, utilities, and urban planning. These systems rely on vast amounts of data generated by sensors, IoT devices, and real-time analytics to optimize operations and improve quality of life for urban residents. The cybersecurity model designed for smart transport systems serves as a crucial component in this larger ecosystem by protecting the integrity and security of transportation data, while also ensuring seamless communication between smart transport systems and other smart city services.

For instance, as smart transport systems share data with public safety networks, healthcare systems, and energy grids, the cybersecurity framework must be capable of handling complex interactions and ensuring secure data flows between various stakeholders. The model's ability to integrate threat intelligence sharing through blockchain technology ensures that all systems in the smart city ecosystem can collaborate effectively in managing risks. By sharing real-time information about emerging threats across various digital infrastructures, the model enhances the city's overall cybersecurity posture, allowing authorities to respond more quickly and efficiently to any potential cyber-attacks (Maldonado Silveira Alonso Munhoz, et al., 2020, Osundare & Ige, 2024, Sanyaolu, etal., 2024). This integration ensures that vulnerabilities in one part of the system do not lead to cascading failures across other systems, contributing to the overall resilience and reliability of the smart city as a whole.

Furthermore, the model's scalability ensures that as a city's digital infrastructure expands, the cybersecurity framework can adapt to new technologies and increased data volumes without compromising performance. For example, the addition of autonomous vehicles or the expansion of IoT-based transportation sensors can be easily incorporated into the existing model without significant changes to the core cybersecurity protocols. This adaptability makes the model an ideal solution for cities aiming to grow their smart infrastructure while maintaining robust protection against evolving cyber threats.

The implications of such an advanced cybersecurity model also extend to policy and governance, particularly in the development of regulatory frameworks that are designed to secure smart transport systems and ensure their safe integration within urban environments. Governments and regulatory bodies must play an active role in shaping policies that provide clear guidelines for the protection of critical transport infrastructure from cyber threats (Adeniran, et al., 2024, Osundare & Ige, 2024). The proliferation of IoT devices and interconnected systems makes it essential to implement comprehensive regulations that address issues such as data privacy, network security, and the sharing of threat intelligence across systems. A well-defined policy framework would ensure that all stakeholders—government agencies, private sector partners, and the public—are aligned in their efforts to safeguard smart transport systems.

Recommendations for regulatory frameworks should include the development of minimum cybersecurity standards for all components of smart transport systems. These standards would outline security requirements for IoT devices, data storage, communication protocols, and user authentication. Additionally, policies should mandate the implementation of continuous security testing and auditing to identify vulnerabilities before they can be exploited by cybercriminals. As smart transport systems rely heavily on data exchange, policies should also include guidelines for ensuring that sensitive personal information is securely encrypted and that access to this data is controlled through mechanisms such as multi-factor authentication and role-based access controls.

Governments should also encourage the establishment of industry-wide collaborations between technology providers, cybersecurity experts, and public authorities to share knowledge and best practices for securing transport systems. This can be achieved through initiatives such as cybersecurity information sharing platforms, joint research, and development programs, and industry-wide cybersecurity certifications (Bello, Ige & Ameyaw, 2024, Samira, et al., 2024). Policymakers should also recognize the need for continuous capacity-building programs for cybersecurity professionals, ensuring that the workforce is equipped with the necessary skills to protect evolving transport infrastructures from increasingly sophisticated cyber threats.

Furthermore, as cybersecurity in smart transport systems intersects with broader national security concerns, it is essential to establish international cooperation on cybersecurity standards and protocols. Transport systems in one country may be vulnerable to attacks originating from abroad, and coordinated international efforts will be required to address cross-border cyber threats. Through global collaboration, countries can align on cybersecurity standards, share threat intelligence, and develop joint strategies for mitigating the risks posed by cyber-attacks.

The advanced cybersecurity model for smart transport systems offers substantial applications and implications for the growth of secure, resilient, and efficient urban mobility. Its integration into smart cities ensures that transport systems can function seamlessly within broader city infrastructures, enhancing both operational efficiency and public safety. By securing data and providing real-time threat management, the model fosters public trust, encouraging greater participation in smart transportation solutions (Adeniran, et al., 2024, Ishola, 2025, Osundare, et al., 2024). Furthermore, its role in informing policy and governance ensures that the regulatory environment keeps pace with the technological evolution of smart cities, creating a safe, sustainable, and secure digital landscape for future generations.

2.6. FUTURE WORK

The future of an advanced cybersecurity model for protecting smart transport systems against emerging threats holds immense potential as technological landscapes continue to evolve and new risks emerge. The progression of digital technologies, including the Internet of Things (IoT), artificial intelligence (AI), machine learning, and data analytics, is making smart transport systems more interconnected, dynamic, and efficient. However, this increasing complexity also introduces novel cybersecurity challenges that must be addressed to safeguard the critical infrastructure that underpins modern cities (Ajakwe, Kim & Lee, 2023, Segun-Falade, et al., 2024). Looking ahead, several key areas of focus will help drive the continued development of robust cybersecurity solutions to protect these systems from emerging threats.

One of the most pressing areas for future work lies in the integration of quantum-safe encryption methods into the cybersecurity model. Quantum computing holds the potential to break many of the current encryption methods used to secure data transmissions, including those commonly deployed in smart transport systems. With the advent of quantum computers capable of solving complex mathematical problems exponentially faster than classical computers, traditional cryptographic techniques like RSA and ECC could become vulnerable to attacks that compromise the confidentiality and integrity of sensitive data. This poses a serious threat to smart transport systems, which rely on secure data exchanges between vehicles, infrastructure, and control systems.

To address this challenge, future research and development efforts will need to focus on developing and integrating quantum-safe encryption algorithms into the cybersecurity model. These algorithms are designed to withstand the computational power of quantum machines, ensuring that critical data remains secure even in a post-quantum world. Several quantum-resistant cryptographic schemes, such as lattice-based encryption and hash-based signatures, are already being explored by the cybersecurity community (Cadet, et al., 2024, Ojukwu, et al., 2024, Zemlyak,Nozdreva & Sivakova, 2024). Integrating these techniques into smart transport systems will require collaboration between cryptographers, cybersecurity experts, and transport infrastructure developers to ensure compatibility and scalability across diverse systems. The adoption of quantum-safe encryption will not only enhance the resilience of smart transport systems but also future-proof them against the impending rise of quantum computing.

Another key area for future work is the development of self-learning systems capable of adapting to evolving cybersecurity threats. As cyber-attacks become more sophisticated, relying on static defenses is no longer sufficient to protect complex systems like smart transport networks. In response, machine learning and artificial intelligence are increasingly being deployed to detect and respond to cyber threats in real-time (Ishola, 2025). However, for these systems to be truly effective, they need to go beyond pre-programmed threat signatures and instead evolve continuously based on new data and threat patterns.

Self-learning systems can improve the accuracy of threat detection by recognizing anomalous behavior that deviates from normal system operations. This approach allows the cybersecurity model to detect emerging threats without relying on previously encountered attack patterns, making it more agile and adaptive to new and unknown risks (Adeniran, et al., 2024, Gouiza, Jebari & Reklaoui, 2024, Idemudia, et al., 2024). By leveraging reinforcement learning techniques, for example, a cybersecurity system could learn from past incidents and continuously refine its strategies for identifying and mitigating threats. Additionally, the integration of AI-powered decision-making systems could enable autonomous responses to threats, such as isolating affected systems or triggering predefined containment protocols, thereby reducing the need for human intervention and improving the speed of response.

The development of self-learning systems will also improve the model's scalability. As smart transport systems become more complex with the integration of autonomous vehicles, electric vehicles, and advanced traffic management technologies, the cybersecurity model must be able to handle increased volumes of data and interactions. Self-learning systems will be better equipped to manage this complexity by evolving in tandem with the growing size and intricacy of the system, ensuring that the cybersecurity model remains effective as the environment changes.

In parallel, another important area for future exploration is the application of the cybersecurity model to other critical infrastructure domains. While the current focus is on protecting smart transport systems, the underlying principles and components of the model are highly adaptable and can be applied to other sectors that rely heavily on digital technologies and interconnected systems. Critical infrastructures, such as energy grids, water supply systems, healthcare networks, and telecommunications, are increasingly vulnerable to cyber threats as they undergo digital transformation and become more interconnected.

For instance, the energy sector is already witnessing the rise of smart grids that use IoT sensors and AI to optimize energy distribution and consumption. These systems are vulnerable to cyber-attacks that could lead to power outages, equipment damage, or even disruptions in essential services. Similarly, healthcare systems are becoming more reliant on digital health records, telemedicine, and medical devices, all of which create new attack surfaces for cybercriminals (Adeniran, et al., 2024, Gouiza, Jebari & Reklaoui, 2024, Idemudia, et al., 2024). Applying the advanced cybersecurity model developed for smart transport systems to these domains would help secure critical infrastructures from emerging cyber threats, ensuring the continued availability, reliability, and safety of essential services.

By leveraging the same principles of anomaly detection, blockchain-based threat intelligence sharing, zero-trust architecture, and real-time response mechanisms, the cybersecurity model can be tailored to meet the unique needs of different sectors. For example, in the energy sector, real-time monitoring and automated response mechanisms can be used to detect and mitigate attacks targeting energy distribution systems, while the healthcare sector can benefit from robust encryption methods and identity verification protocols to protect patient data. In each case, the model would be designed to address the specific vulnerabilities and risks faced by each critical infrastructure, enabling a more secure and resilient digital ecosystem.

The integration of the cybersecurity model across various sectors also presents an opportunity for cross-sector collaboration in threat intelligence sharing and risk management. The lessons learned from securing smart transport systems can be shared with other industries facing similar challenges, fostering a collaborative approach to cybersecurity. By creating a shared pool of threat intelligence across critical sectors, organizations can better identify emerging threats and coordinate responses, ultimately enhancing the collective resilience of interconnected systems (Adeniran, et al., 2024, Gouiza, Jebari & Reklaoui, 2024, Idemudia, et al., 2024).

In addition to expanding the scope of the model to other sectors, future work will also need to focus on regulatory and policy considerations to support the widespread adoption of advanced cybersecurity models. Governments and regulatory bodies will need to establish comprehensive frameworks for cybersecurity across critical infrastructures, ensuring that industries are held accountable for implementing robust security measures and that there is a clear standard for assessing the effectiveness of cybersecurity strategies (Cadet, et al., 2024, Ofoegbu, et al., 2024, Ishola, 2025). International cooperation will also be essential, particularly for sectors like transport and energy, where cyber threats can have far-reaching global implications. Collaborative efforts to harmonize cybersecurity standards and regulations across borders will help create a more secure and interoperable global infrastructure.

Finally, continuous monitoring and evaluation of the cybersecurity model will be critical to its long-term success. As new threats emerge and technologies evolve, the model must be regularly updated and refined to stay ahead of adversaries. Ongoing research into emerging technologies such as AI, quantum computing, and blockchain will play a crucial role in shaping the future of cybersecurity, enabling smart transport systems and other critical infrastructures to remain secure in an increasingly complex digital landscape (Adeniran, et al., 2024, Gouiza, Jebari & Reklaoui, 2024, Idemudia, et al., 2024).

In conclusion, the future work for an advanced cybersecurity model for protecting smart transport systems against emerging threats is expansive and multifaceted. From integrating quantum-safe encryption methods to developing self-learning systems capable of adapting to evolving threats, there is significant potential to enhance the security of critical infrastructure. Furthermore, by applying the model to other sectors and promoting cross-sector collaboration, the cybersecurity framework can help safeguard the broader digital ecosystem (Adeniran, et al., 2024, Ogunsina,et al., 2024). The continued evolution of the cybersecurity model, combined with strong regulatory support and international cooperation, will ensure that smart transport systems and other critical infrastructures remain resilient and secure in the face of emerging cyber risks.

2.7. CONCLUSION

In conclusion, the development and implementation of an advanced cybersecurity model for protecting smart transport systems against emerging threats represents a crucial step towards ensuring the safety and resilience of modern mobility solutions. As smart transport systems become increasingly integrated with IoT, AI, and data analytics, the potential vulnerabilities in these complex networks grow, making the need for robust cybersecurity measures more critical than ever. The proposed model incorporates innovative technologies such as anomaly detection, blockchain-based threat intelligence sharing, zero-trust architecture, and real-time response mechanisms, each playing a pivotal role in addressing the evolving landscape of cybersecurity threats.

Through a comprehensive approach, the model improves the overall security posture of smart transport systems by providing scalable and adaptable solutions for detecting, preventing, and responding to emerging cyber threats, such as ransomware, DDoS attacks, and advanced persistent threats. Its focus on real-time threat management, continuous learning through machine learning, and proactive risk mitigation creates a dynamic and resilient cybersecurity infrastructure capable of defending against both known and unknown threats.

Moreover, the model's emphasis on collaboration and information sharing, particularly through the use of blockchain technology, facilitates a more integrated and transparent approach to cybersecurity. By leveraging collective intelligence from multiple sectors, the model enhances threat detection and mitigation efforts, allowing stakeholders to respond more effectively to the global nature of cyber-attacks targeting critical infrastructure.

As we look toward the future, the model serves as a blueprint not only for smart transport systems but also for other critical infrastructure domains, such as energy, healthcare, and telecommunications. Its principles of security and resilience can be adapted and expanded, fostering a broader ecosystem of protected, interconnected systems. The integration of quantum-safe encryption, self-learning systems, and ongoing research into emerging technologies ensures that the model remains agile and capable of evolving in response to future cybersecurity challenges.

Ultimately, this advanced cybersecurity model will play a fundamental role in advancing secure and resilient mobility solutions, contributing to the long-term sustainability of smart transport systems and their seamless integration into the broader smart city ecosystem. As these systems become more embedded in daily life, ensuring their protection against cyber threats is not just a matter of security but of public trust and confidence in the digital infrastructure that powers modern societies. Through continuous innovation and collaboration, the cybersecurity model can safeguard the future of mobility, enabling safe, efficient, and resilient transportation systems that meet the needs of both today and tomorrow.

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