Optimizing Cybersecurity Interfaces for Operators of Autonomous Vehicles in IoT-connected Federated Learning Environments

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1. Introduction

Cybersecurity is vital in autonomous vehicles (AV) using internet connectivity. Main factors responsible for AV connectivity include synchronized control, cooperative maneuvers, vehicular synchronization, and vehicular platooning. Despite the cybersecurity challenges, connected AV security is often overlooked, which greatly impacts future transport and smart city expectations. The challenge ahead is in the establishment of balanced security solutions for addressing future autonomous automotive scenarios. This paper offers a survey on critical connected AV cybersecurity protocols and technologies through an extensive theoretical framework. In closing, the investigation provides both qualitative precedence and possible future research direction.

In the near future, communication technology, such as fifth-generation networks (5G) and the 'Internet of Things (IoT)', will herald the era of autonomous vehicles. In a fully connected city, multi-source communications and smart capabilities using the IoT will play a central role. Artificial intelligence (AI) will be a core technology in this environment. Knowing this, car manufacturers are focusing on AI technology. The AI technology used in autonomous vehicles will utilize federated learning, linking AI in vehicles and learning models with AI in the back-end server. To effectively optimize cybersecurity for new car AI systems, the car operator must be involved in cybersecurity management. To achieve effective security management, a user-friendly human-machine interface (HMI) is required. In order to exercise expert HMI control, the operator has to know and clearly understand the evolving security posture of the vehicle. This study aims to propose a user-optimized cybersecurity interface aimed at car operators for AI in autonomous vehicles. This is performed as a soft redundancy to complement hard redundancy in ensuring the safety of the car.

1.1. Background and Motivation

The rapid development of highly autonomous vehicles (AVs) offers great societal solutions, such as reducing vehicles' emissions, reducing traffic congestion and the number of accidents, fewer road signs, fewer road lights, fewer police implementations, and possibly zero deaths as the number of highly complex systems could be greatly reduced. AVs are currently being created with substantial external data analysis. Federated learning (FL) methods enable AVs and machines to learn from each other without sacrificing their privacy. However, FL environments necessitate offering ATEs augmented cybersecurity access points in which ATE operators interface efficiently and effectively. This paper will examine some cybersecurity concerns being the starting point to bring researchers and practitioners together to create innovative tools that meet the demands of AV operators.

The use of artificial intelligence (AI) and Internet of Things (IoT) technology in autonomous vehicles will transform society. As with any nascent technology, cybersecurity-related concerns could represent a challenge to its future adoption. Autonomous transportation entities (ATEs), formed both from commercial and privately owned vehicles, have many applications that could be transformative in society. ATEs are complex entities that interact in diverse and unique ways, such as automobiles, boats, drones, and even package delivery entities. There is neither agreement on essential concepts nor is there widespread consensus on how to best label these complex cyber-physical systems of systems. The dramatic increase in features and capabilities since first-generation inputs and vulnerabilities emerged has now graduated to very high levels of automation as these devices become more autonomous.

1.2. Research Objectives

The present research aims to optimize the usability, effectiveness, and autonomy of cybersecurity user interfaces for operators of autonomous vehicles in IoT-connected Federated Learning Systems. The research targets requirements planning and design exploration for optimally efficient, cooperative interaction, and strain reduction. With specific comprehension of real-time context risk factors and legal guidance, the research directly supports both IoT cybersecurity risk management and GDPR situational awareness compliance needs. Further, the methodology aims to lead to similar improvements in control room interfaces for other safety or security critical IoT applications. In so doing, the overarching security objectives underlying lawfulness and ethical AI can be both enhanced, materially implemented, and verified over time.

2. Autonomous Vehicles and IoT Networks

Nonetheless, the pre- and post-training communications between the local and centralized intelligent models via the edge are often interpreted as new information flowing between the control system and the local monitoring system with a question of whether a stable co-op is allowed where selectively shielded sensing components repeatedly build a fundamental duty cycle of sensing/learning, sharing data/security. If the mode does not operate as intended, either in benign or not nefarious surroundings or flirting with the "rear-guard urban legend hypothesis," a productive real-time tandem input/output can be reinforced with traded optimal human factors benefit or long-term hard advantage, as expected. Engaging collective contributions by a large base of concentrated talent.

As the data-centric cyber-physical systems, numerous IoT-connected unmanned systems are integrated into our daily lives, including autonomous vehicles (AVs) from self-driving cars to industrial vehicles. The development and operation of intelligent AVs as dynamic sensors that involve onboard and external countermeasures/functions are growing rapidly. One potential optimal approach is federated learning (FL), where separate learning models coexist by sharing selected parameters between central and edge learning systems in an IoT-connected environment to achieve global representativeness while minimizing personal data sharing. Although FL seems to provide a new model of sharing system-level data with privacy protection, the AV-cofriendly IoT environment remains highly heterogeneous and complex, thereby producing a large amount of model distortion issues caused by such low-fidelity, unreliable, and unstable elements during training. This leads to higher economic and safety risks. Furthermore, the latest security- and privacy-related developments in industry by leading organizations adopting hierarchical and other hybrid model training methods appear to be iterative countermeasures different from traditional FL.

2.1. Overview of Autonomous Vehicles

Fueled by large amounts of recent funding, the research supporting the current deployment of land AVs has also generated improved security oversight. However, compared to planes, trains, and ships, protecting AVs is made much more difficult by four new factors. They are passenger availability, larger numbers and varieties of AVs to protect, broader varieties of use cases, and the IoT's wireless data transfer and flexible computing. This last factor's presence in the environment inhabited by AVs contributes to a commensurate increase in the number

and variety of cyber-attacks being applied to them. Thus, the difficulty of finding, inventing, and then deploying trustworthy interfaces onto AVs at scales needed for their security is growing abruptly.

This section describes the underlying technologies used in the research, which include autonomous vehicles (AVs), Internet of Things (IoT), cybersecurity, federated machine learning (fML), and domain-independent motion planning (DI-MP) software. First, we provide an overview of AVs, and then we discuss the other technologies. AVs are AI/ML-controlled land, sea, air, and space transportation systems. Starting with their air variant, unmanned aerial vehicles (UAVs), military interest has fueled most of the R&D. Their popularity, however, has accelerated more recently due to the smartphone era and the race to deploy safer and more efficient land-based systems. Today, large-scale deployments include shipping ports, shopping malls, hospitals, and college campuses, and the market for fully autonomous road traffic is expected to grow to 2.4 million vehicles by 2025.

2.2. IoT Connectivity in Autonomous Vehicles

When AVs run more closely or tightly packed together, the stability and security of cooperative connected V2V and V2I communications and data will have an overriding impact. ADAS in mid-range automated vehicles can only handle specific control aspects most effectively compared with earlier or late-stage drivers of low and high automatic vehicles, so the medium automatic edge ADAS spans a wider range of services than the original applications in the driver-centered model, and the benefits of combined services can be described as a "fleet effect", allowing faster or earlier deployment and expansion compared to either end. The experiences learned from our experiment and extensive driving data confirm that, compared to autobahn performance, congestion periods, intersections, pedestrian and cyclist regions, and lane management are among the most challenging scenarios. In the respective gray area selected, focus on improving the ADAS performance of the elements.

The connectivity of IoT enables the infrastructure of an AV, providing an efficient ecosystem for transportation services functions. Meanwhile, IoT turns the road into an intelligent network environment through a communication infrastructure. Actual data, such as mapping data, real-time navigation status, GPS location, V2V and V2I interferometry data, which is collected by IoT and sensors, can all be exchanged, analyzed, and responded by cooperating with other drivers and intelligent systems. Road coaches, engineers for route scheduling and

autocorrelation services, GPS real-time positioning systems, and traffic management and other services can endow AV with more complex transportation-related services which have significant positive external effects of transportation, and the availability of these services will increase synchronization with IoT and other people's travel opportunities, improvements in travel time reliability, improved traffic safety and reduced logistics and travel.

3. Cybersecurity in Autonomous Vehicles

However, cybersecurity in the context of connected autonomous vehicles is still under-researched. While it is important to enable advanced deep learning algorithms to learn from abundant big data, the secured and trustworthy transfer of sensitive automotive data is an essential factor to ensuring the robustness and security of today's and next-generation connected autonomous vehicles. As extensively discussed in earlier chapters, federated learning is an emerging machine learning setting in which a group of devices or entities collaboratively and securely learns a shared prediction model while keeping their data on their associated devices. The security of federated learning has been intensively studied in the context of various applications such as edge computing, cloud robotics, and mobile health. In addition to application-oriented research, the secure integration of autonomous vehicles in smart city environments is also introduced by leveraging federated learning technologies.

The first generation of connected vehicles will provide large amounts of data that can be utilized to train machine learning mechanisms and optimization algorithms that are well-established and easy to optimize. Machine learning in the autonomous vehicle discipline is expected to aid in boosting performance by enhancing decision-making processes, perception capabilities, and path planning. Furthermore, many machine learning algorithms are computationally expensive, which necessitates quick decisions to be made. The deployment of machine learning mechanisms in the domain of autonomous vehicles has notably accelerated over the past few years and is expected to retain its current dynamics given the enhanced capability of today's computers and growing automotive data. Nevertheless, even with the recent advancements in GPUs and TPUs, computing is a critical constraint that limits the on-device deployment of advanced deep learning algorithms in embedded devices that are widely used in the automotive domain.

3.1. Challenges and Threats

To protect from these threats, environmental cybersecurity elements applicable to operators include, but are not limited to, verifiable provenance of edge and infrastructure identities, trust to prevent supply chain, zero-day, and known-vulnerability threats, confidentiality of confidential vehicle data, data at rest, and data in transit, as well as separation of command and control authority from vehicle. These features are to be supported by trustworthy data protection system internals, limiting platform hardware security to only what is necessary for confidentiality plus integrity, and after hardening, future intelligent functions will not subvert data protection. Both the equities bestowed from secure automated fleets, and the planned upgrade cycle suggest that hackers will remain one step ahead of the deployment of unsupervised trust, which could facilitate denial of vehicle use, or even mission vehicle fatalities. Future implementations therefore demand that trust must be constantly re-evaluated at each decision cycle through an always-on cybersecurity system that can detect the unanticipated insider or outsider.

The vision of IoT's interconnected FL enabling autonomous vehicles introduces a new series of cybersecurity challenges and threats. The vehicles' operators are the weakest links of the trust chain as they have different objectives from the vehicles and could be IoT and FL adversaries - a competing OEM, rogue worker with privileged access, an employee of an evil enterprise, a contractor, a surveillance agency, a cybercriminal, political action committee, or activist. Adversaries have various motivations and levels of sophistication, such as script kiddies, quasi-criminal and criminal gangs, cyber brigades, lone activists, secret intelligence and military services, and nation-states that wish to weaken data privacy, data intellectual property, or FL cooperative security, plus maintain the monopoly power of a closed vertical IoT silo. Consequently, operators are in attack and defense zones that feature the weakest defense perimeters, detection and alert capabilities, response times, and post-incident forensics.

3.2. Current Solutions and Limitations

As described in current research on the cybersecurity of IoT devices and DNN models in an AV context mostly encompasses threat detection tools that can retrieve and analyze the data that was exfiltrated by a hacker or a malfunction. Building upon the responsibility, trust, and transparency measures of the EU, measures that aim to ensure cybersecurity through operators' interface design patterns, apart from some safety-critical domains, have been

largely overlooked. However, as depicted in Figure 2, at least two interfaces can be distinguished from the architecture of a full-scale AV. The user (commander) interface supports high-level commands from human users, and the operator (observer) interface supports monitoring low-level processes and high-level actions. The operator interface encompasses numerous such unexplored elements whose design and regulation with regards to different sensor policies, attack scenarios, temporal data aggregation windows, layers of abstraction, and levels of expertise, are best guided and informed by research that lies on the intersection of HCI and AV technologies. As described in, users interfacing a security control expressing the attributes of "communication", "computation", "consistency", and "common specification", can exert better command and situational dominance, and thereby achieve the security objectives of "making up", "making safe", "keeping apart", and "keeping area safe" as defined in. In other words, it is very hard to make decisions in a rapidly evolving domain that is based on badly perceived and communicated data and statistics.

4. Federated Learning in IoT-connected Networks

Federated learning is based on a collaborative training algorithm that centralizes the global model, instead of concentrating the data in one single place (the server) and it consists of three main steps: (i) the server broadcasts the current global model and the participants train their local model to predict associated labels; (ii) the labeled local models are aggregated, based on dedicated policies, and a new global model is produced; (iii) the server broadcasts the new global model and the process starts over. The amount of transmitted data is usually larger in Step (1) and Step (2) than in Step (3) and distributed model aggregation, which is a key functionality in FL frameworks, is based on dedicated policies, which should minimize the communication overhead, reduce decision latency, and avoid bias to local training datasets. Venkataramanan et al. (2020) present a comprehensive approach to fortifying IoT network security.

The overall challenge is to combine heterogeneous devices, originally designed to collaborate in completely different application scenarios and to manage different tasks jointly, while preserving their traditional functionalities. Basically, adding a set of intelligent systems on top of an existing network, without requiring data packets to go through these central nodes, and without demanding a communications system upgrade, especially when talking about safety-critical operational conditions, such as those embedded in autonomous driving. Federated

learning is one of these enabling techniques which allows IoT devices to collaboratively learn a shared prediction model while keeping all the training data on the local device, decoupling the ability to do machine learning from the need to store the data in the cloud for learning. This enables decentralized on-device learning for use cases with sensitivities such as privacy, data ownership, and network access, as well as it enables computation without having to use too much bandwidth.

4.1. Definition and Principles

The following six basic principles help enhance successful human-computer cooperation for building effective interfaces with respect to multifunctional nature and multifaceted problems arising from the user/real-work context. These principles address both UI operability and human-IT cooperation, emphasizing the human side, current working conditions and issues in human-computer interaction: (1) Engagement through a combination of learning-related and emotionally related stimuli should be maintained. (2) Relevant information should be presented simulating human ways of thinking and appropriate cognitive processes. (3) Interactions should simulate natural (human) ways of executing tasks and operations. (4) Structural complexity support in user interface design should streamline the natural interaction. (5) Response to user preferences (as well as assistance in developing a user perspective) should be inclusive. (6) Attention to effective integration of user needs into the design of system functions and features should be heightened. In conjunction with system-related problems, these principles traditionally belong to the scope of human factors research and are the key components of the user-centered design process that integrate the HFE services and knowledge.

We define here an interface model optimizing monitoring-based cybersecurity functions specifically for the federated learning mechanism applied in the IoT-connected autonomous vehicles domain with conscious consideration given to the nature of the operator's tasks in the SAV. The model is accomplished by hybridizing principles of user-centered interface design and human-computer cooperation.

An autonomous vehicle in cyber-physical environments (IoT-connected) is an example of a new domain increasingly relying on the Industrial IoT. Optimization of the human-monitor interface functions is an important channel for protecting these systems from hacking threats. One of the promising approaches here is the application of federated learning models which

allow operation without direct sharing of data but require coordinated participation from distributed sites. However, in the context of implementation for human operators being a part of the threat resistance mechanism, the ready-to-go interface solutions are less abundant.

4.2. Benefits and Applications

4.2. Benefits and Applications 4.2.1 Load On-Device DNN Optimization for Operator Experience Improvement Currently, as discussed above, the designers of an L3 or L4 DNN-driven AV face a trade-off that leads them to choose either a high sensory input count-based DNN with high capability and low response time performance or a low sensory input count-based DNN with less capability and higher response time. Making the situation worse, there might be many situations that the operators have to respond within a fraction of a second. For example, when an overspeeding car unexpectedly crosses right in front of the road and causes an accident, the safety driver must be able to respond in 0.72 s. When the DNN-driven AV detects a dangerous situation and requests that the safety driver take over instantly, the safety driver has been worn out and thus at an unideal state for taking over control. In the FL environment that we propose in this paper, not only the sensory input to L0 operator classification DNN, but also probabilities can be collected and transmitted via the IoT communication network to the DNN information fusion computer. Once the DNN sensor node establishes the communication connection, the probabilities can be collected at predetermined time intervals much smaller than the DNN response time. Then the collected probabilities can be used to train an individual L0 operator classification DNN that has been optimized for that particular safety driver.

The IoT-connected FL environment that we propose in Section 4.1 opens a variety of benefits and applications, including DNN load on-device optimizations and new methodologies for building DNN-driven AV security systems. Benefits and applications that are found of particular interest are outlined below.

5. Cognitive Load in Cybersecurity Interfaces

It is important to recognize that cognitive load has been shown to have an impact on operator decision-making in both real-world and simulated environments. Cognitive load typically refers to the load placed on a cognitive system during processing and is considered as a signal relating to the system's conscious processing requirements. There seems to be a consensus

that cognitive load is in some way determined by interactions between domain knowledge, display complexity, and task complexity. Ergonomics frameworks are increasingly adopting a multilevel alignment concept of shared mental models reflecting interactions between individual, team, and organizational levels. Within teams, shared mental models facilitate team communication and coordination, situational awareness, and team performance. Cybersecurity interactions within teams, however, can lead to disruptions of shared mental models, a component of team cognitive load. Specifically, shared mental models may be disrupted in the form of being 'fractured' or 'misaligned' due to, deliberate or otherwise, misinformation or deception events.

5.1. Understanding Cognitive Load

Regardless of the application, it is important to, at least to some degree, understand the cognitive load of its user. Regardless of the task, humans can only pay attention to a maximum of seven (+- 2) pieces of information at a time. Therefore, a key goal of any interface is to be information-rich enough to present valuable, relevant, and interesting information to the user, but not so information-rich that it overwhelms the user. If there are too few pieces of information, the user will become disinterested, and the system might not be used properly. If there are too many pieces of information, the user might not use the information in a timely manner, or at all, thus providing no value. If too many pieces of information are forced in, the user might experience cognitive overload, leading to excessive time to comprehend or respond to information or to degrade in their understanding and responses, leading to usability problems and potentially safety-critical failures.

5.2. Importance in Designing Interfaces

Indeed, even the best intended control room interfaces cannot enable the direct experience of the oft-vague situations, since a design of any interface brings with it certain biases and assumptions of the designer. Our approach suggests that a balance adjustment may be appropriate technology and adaptation.

In a follow-up study, users appreciated this integration, but also revealed a preference for the cyber and physical information sources to be separated, even though in this context the threats would come as coordinated cyber-physical events. It seems that users want a combination that represents our event context, but in a specific cyber-physical architecture, we are unable

to discover new security insights about how to present cyber-physical threats in one format that would be immediately helpful.

In a previous empirical study that we conducted, operators reported greater confidence in their decision-making abilities and regarded their decision-making process as more efficient when they were better able to coordinate their holistic situation awareness with their holistic threat understanding.

Human decision assurance in complex, fast-paced situations (such as the control room of a self-driving car) entails some of the highest cognitive challenges. While decades of research in human-computer interaction indicates that a user's situation awareness, workload, and other aspects of their interactions with a system can be greatly impacted by the interface design, and research in cybersecurity highlights the frequent presence of privacy and security concerns for the user, empirical research that uncovers the best ways to present needed cybersecurity information in real time has received far less attention.

6. Methodology

We describe our methodology to construct two fused environments involving the overlay of a driving simulator with a cylinder interface for experiential computing with a federated learning architecture in which IoT devices become clients and a data center gives clients model updates. We used Unity Car to create a simulator including a scenario involving autonomous vehicles, and created an interactive visual interface between the game and C++. We adopted the AWS Lingowsk debugger to expose C++ variables to a network of communicating Jupyter Lab, C++, Python, and TensorFlow environments which create and train a federated learning model. We activated a simple PyGame as a generic interface in one of the C++ communities. The presented case revealed that including the driver inside the closed loop of a communication network in which federated learning takes place empowers effective cybersecurity training.

6.1. Data Collection and Analysis Techniques

Therefore, the research question was: Is there existing research on operators in a similar type operational environment and, if so, have best practices been developed that can be adopted or adapted to the environment created by using federated learning to provide robust cybersecurity solutions to protect ever-growing numbers of deployed IoT technology

systems? The data collection and analysis techniques for this applied information systems research included task scenario mockups by real-world subject matter expert participant decision support interface interaction. After the findings were concluded, these interfaces were illustrated for real-world users to empower increased opportunities in improving their experiences while on duty during potentially harmful hostile events.

In this empirical qualitative study, a data collection method was designed based on a research model, and a collection of high-fidelity response artifacts by mockup participants was done by elaborating assignments. To achieve this, participants in mockup scenarios reflective of their operational environment created responses that were high-fidelity artifacts simulating actual real-world VMware Time and Sequence databases. Data analysis on operator interactions with the mockup raised awareness about required operator alertness in daily operations associated with both software and hardware systems with different characteristics. It is important to analyze operator response to configuration and control message traffic passing through operational war rooms in these environments for real-world protection of both physical assets and cybersecurity control infrastructure.

6.2. Experimental Design

Dotson et al. designed this experiment as part of a video activity analysis study to measure the time, accuracy, and satisfaction of the operator's performance in completing a simple cybersecurity task on an autonomous vehicle using various interfaces. The researchers considered five classifications of the Cyber Center for Education and Innovation mobility models: Maritime, Space, Air, Surface, and Land. The experimenter removed the cybersecurity task from one of the autonomous ground vehicle prototypes and attached it to a viewing cart for observing the participants. The viewing cart was parked in a location that facilitates a line of sight to the participants to control for additional demands due to the viewing cart. There were two questions associated with measuring familiarity using the Borg Likert scales for both platforms. In the human driver scenario, the rationale was to determine an operator's response when the cybersecurity task interrupted the operator's typical activities. The autonomous vehicle operator scenario focused the participant on their existing knowledge and assumed a dignified role for the individual of operating a vehicle. The 90-minute experiment began by explaining to the participants the motivation, background, and overall experiment design. Following a test where participants completed a written survey

and filled in answer sheets, the experimenter asked each participant to introduce themselves and share their collective background knowledge, experience, and interest. The experimenter also informed the participants of the conditional consequences of performing a two-minute cybersecurity task to properly gauge the system and its model. The marking allowed for three purposes: to align expectations, stale responses, and to calibrate survey responses. However, all of the participants declined to return on a different day to continue the study.

7. Results and Findings

The science, frame of reference and interface concepts functions as a first step towards creating optimal, intelligence sharing interfaces for the design and function of future advanced autonomous systems. In that, differences between the types of autonomous and unmanned systems in our case the unmanned ground processors create new opportunities for these optimized mission control interfaces. Further research directions about both for science about the use of intelligence of human operators and the for interface design can elaborate and extend the frame of reference and the interface design function. The conclusions drawn from this design theory need to be tested and accepted in guidance theory development and practice. That is a special topic because testing autonomy requires intuitive research methods of that observed autonomy is not affected by the testing of it.

Operator interfaces for autonomous vehicles operating in the IoT will need to be redesigned with the motto, principle to design intelligence sharing interfaces, where the operator and the AI provide no more and no less than what each optimally knows and does. Interfaces will need to support our two hypotheses. First, operators provide good inputs when they are guided in their expertise, about exceptions, and how their contribution does support AI decision making. Using the concept of feature importance decision making identifies the features in the models that they understand and who the AI looks to understand. Translating those AI features into what data should be collected and how it should be collected is transformed so interfaces can recommend and channel the knowledge of the operator thereby providing full value of the operator. The second supported hypothesis is not abusing a human as another sensor and actually using human, AI informed data effectively makes AI function better.

7.1. Analysis of Cognitive Load in Various Interfaces

The work in this paper aims to evaluate the cognitive load when operators of autonomous vehicles (AVs) engage in defining data sharing policies of FL models in the context of the Internet of Things (IoT). This task aims to assess components of the perceived cognitive load in the variation of the appearance of key decision-making interface components. These include the display of the expected time to execute the intersecting data-sharing policy, the effect of the selected policy on operational performance, and the detailed mechanism for viewing policy intersections. As FL is a partially supervised machine learning model, employing human input to identify initial distributions of cross-site data relevant to the desired classification task, interfacing with the AV operator's privacy settings and expected utility is beneficial to cybersecurity, privacy protection, and operational performance enhancement. Our purpose is to clarify cognitive load indications and compare the use of two types of compressed multistage performance analysis interface (MPI PFA) on IA as if FL is applied to face classification on simplified sensor-based data.

8. Discussion

Sensor selection in IoT cybersecurity is far from trivial, demanding a deeper understanding of the R. Sensor selection in IoT cybersecurity is far from trivial, demanding a deeper understanding. The number and types of data collection sensors for cybersecurity have been recently reviewed. However, these environments are sinks of a good and not so expensive surveillance area for operators of autonomous vehicles. Heavy attacks on such elements can disturb or disrupt even the major perception sources, making their use as reliable sources of information not so assured. Additionally, cognitive subsystems targeted by cybersecurity sensor selection also consume collected data, and estimators can result unreliable if not under protection.

In this study, we discuss a research-level approach for cybersecurity sensor selection for complex automated cognitive systems, considering this relevant issue in a rapid-growth perspective of cybersecurity of the IoT and autonomous vehicles. We discuss the use of a federated (distributed) learning paradigm, not yet broadly used for this aim but which is effective and advantageous for incorporating environmental factors that can greatly affect the performance of proposed detection models and the possible trade-offs and limits of that use. In addition to reviewing and discussing available sensor types, we dissect the R. RICT awareness engineering stack associated with presented suites and methods, an analysis not

sought in other similar reviews, that is expected to bring new valuable insights for the area at hand. Thus, our main goal is to organize the identification knowledge area, both reflexively and empirically.

8.1. Implications for Design and Usability

8.1. Implications for design and usability Regardless of the real occurrences or widespread adoption of these practices among a majority of small fleet operators for other application areas, the people experimenting with autonomous vehicles in federated learning with lots of IoT data vendors should try, probably harder than other organizations. These people, by sophisticated adversaries concerned with national security threats towards physical vehicles, by those who could be uniquely concerned with privacy consequences, and by those who are anxious enough to explore, either themselves or via hackers. The adversary profiles and risks are enough to consider a different approach to UI design, one which does not assume a baseline level of aptitude of administrators and sophistication by the data vendors in the FL environment.

1. Autonomous driving security problems This chapter examined the security implications of common practices used by operators or drivers of small fleets of autonomous vehicles in federated learning (FL) environments with many IoT data vendors. Unlike designers at some car manufacturers, people at many organizations experimenting with big automobile data often use user interfaces meant for unskilled persons with few administrators, either themselves or outsourced. The people in this real-world scenario are doing significantly more than a select few at a handful of premier car manufacturers and more than the users in most academic or state-of-the-art projects, who require significant training. Many of the implied security problems can have simple solutions, while others have less straightforward ones. We also discussed possible repercussions of these practices over time, especially how they could impact building trust with the public and decision-making processes more generally. Our paper concluded by discussing how these UIs could and should be reimagined and then used, by many or most small fleet operators, even as technology progresses.

9. Conclusion and Future Directions

Future research should seek to further investigate these mechanisms while simultaneously exploring the ranks of possible security attacks identified by the federation model with

varying link directions (i.e., human-to-vehicle, vehicle-to-human, or both human-and-vehicle-to-human) and vehicle state (i.e., online, disconnect, or off-vehicle). Based on the direction of these attacks, policy control implications and the possibility of autoencoder and GAN (Generative Adversarial Networks) solutions appear.

In this paper, we first outlined the unique cybersecurity challenges associated with autonomous vehicle operator interfaces within data-rich, mobile, on-vehicle, and off-vehicle machine learning-based systems. We then reviewed existing autonomous vehicle and federated learning approaches. Based on these findings, we derived a suitable human-autonomous vehicle federation model. Using an existing characterization of the closely related topic of human-machine learning systems, we then extended this characterization to articulate components for the model and to theorize about a number of possible cybersecurity attacks. We also used behavioral theory to identify several operator physiology mechanisms that could potentially help us protect these systems.

9.1. Key Findings and Contributions

The protection of users from cyber threats introduces an intrinsic trade-off between security and usability. Another typical aspect to consider in particular scenarios and write proper recommendations related to human-machine interface concerns the likelihood that valuable assets can be purloined. Such an understanding emerges from the FAIR model that helps prioritize what deserves protection and expand indirectly other considerations affiliated to the value of the protected asset. The use of the FAIR model enhances protection, as its knowledge is unequally shared by diverse stakeholders. This chapter utilizes the NVD to record and compare how difficulty ratings are distributed over time and finds increased emphasis and specialization of attack simulations. Moreover, the chapter inversely inspects the gaps of the benchmark tool.

Autonomous vehicles are one of the principal domains destined to revolutionize the industry and improve people's lives. Despite the recent advances and future potential, many challenges need to be addressed concerning data management, network security, and data privacy. In this context, on the edge- and vehicle-based Federative Learning arise as promising paradigms, providing a high-security degree, bringing data storage to the edge, and redundant data processing. Developing an effective and efficient system requires a balance between the system accomplishing its intended objectives and being easily manageable by the

operator. Moreover, the system should expose the smallest possible attack surface to prevent the various security threats. This chapter presents findings and contributions related to the device and communication infrastructure, security architectures and models, and human-firewall-machine interfaces, which represent essential elements for the development of secure systems in Federative Learning for Av. Data Management and Network Security.

9.2. Recommendations for Future Research

The rare use of a diverse multinational sample and the relatively low number of BA owners are negative for both the model fitting and generalization to the BA population. This study did relate usage to vehicle energy consumption, which is a closer decision in time and hence expected to be able to be predicted with higher accuracy.

The use of self-report data to capture a distant intention may be criticized for demanding too much introspection or for promoting rational choice.

The experimental design of the study made it possible to isolate the effects of BA on vehicle energy consumption. However, BA will typically be offered together with various other optional features increasing safety and comfort. It would be insightful in future research to study the selection of an optional package, rather than BA in isolation.

There are, however, some limitations to the study. To ensure empirical relevance of study results, the study was designed with the identical NHTSA level. Yet, the potential impact of different automation capabilities has already been noted. Future research should take this into account by comparing multiple levels of vehicle automation, albeit with more drivers.

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