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A Comprehensive Review on Enhancing Autonomous Transport with Federated Learning and Artificial Intelligence Integration

Y.Pradeep Kumar[1], V.Mustafa[2], G. Sudhakar[3], Kavin FrancisXavier[4], Rajeshwari V[5], Krishnaraj M[6,*]

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Abstract*:* There has been a surprising amount of curiosity about the Internet of Everything (IoE) technologies powered by the sixth generation (6G), such as self-driving automobiles. Federated Learning (FL) in autonomous driving automobiles can open up several intelligent applications. FL offers spread machine learning model development without requiring the transfer of information from the device to a centralized computer; however, it comes with its own set of deployment difficulties, including durability, the safety of the centralized computer, limitations on communication capabilities, and leakage of privacy because unauthorized collection servers can infer confidential data from the devices themselves. The Internet of Vehicles (IOV), which depicts a linked system of automobiles and infrastructure, is one of these devices. IOV becomes an Intelligent Transportation System (ITS) when combined with the latest innovations in computer training and intelligent technology. For effective and privacy-aware automotive social media, researchers provide an autonomously artificial intelligence-based federated learning (AIFL) architecture in which transnational interchange and verification of nearby on-vehicle machine learning (oVML) update models take place. AIFL leverages the blockchain's agreement structure to provide oVML without the need for any centralized information for training or organization. Simultaneously, self-driving and robotic vehicles now have far higher levels of cognition and independence because of Deep Learning (DL). Issues about information safety and consumer privacy have become an unavoidable study priority during these revolutions in technology. With its intrinsic decentralization of the natural world, FL offers an alternative to secure deep learning at the edge by allowing training on data-isolated islands while only sending modifications to the model. Federated teaching and learning is a major ITS enabler with a plethora of applications and advantages. It is expected to be widely deployed in 6G networks for various reasons and technologies..

Keywords: *Artificial Intelligence, Autonomous driving, Intelligent Transportation System, Machine Learning, Federated Learning.*

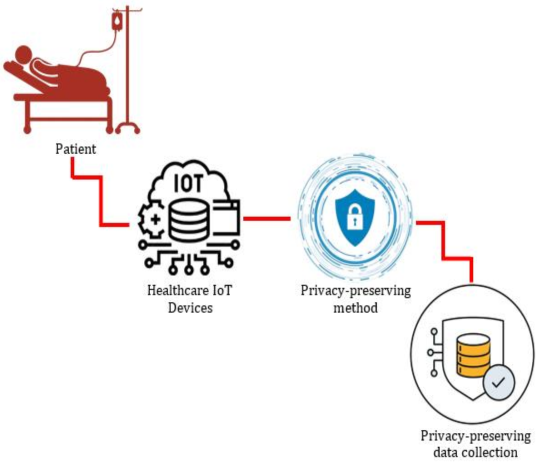
1. Introduction

Several newly developed Internet of Everything (IoE) technologies are going to be made possible by the current trend toward the establishment of sixth-generation (6G) wireless networks [1]. These new IoE technologies include but are not limited to, haptic feedback, brain-computer interfaces, and autonomously linked vehicles [2]. Shortly, self-driving automobiles are anticipated to provide an impressive array of functions due to the astonishing ubiquity of new technology, algorithms may be used to enable these characteristics [4].

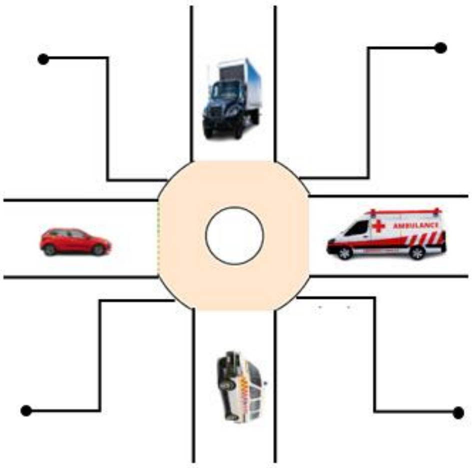
1 Department of ECE, Madanapalli Institute of Technology and Science, Andhra Pradesh, India
ORCID ID : 0000-0003-4697-5818
2 Department of ECE, Madanapalli Institute of Technology and Science, Andhra Pradesh, India
ORCID ID : 0000-0001-7282-1850
3 Department of CSE, Sri Sai Ranganathan Engineering College Coimbatore, Tamil Nadu, India
ORCID ID : 0000-0002-1029-4888
4 Instrumentation Engineer, M/S Muscat Engineering Consultancy Pvt. Ltd, Trichy-620001, Tamil Nadu, India
ORCID ID : 0000-0003-9216-874X
5Department of IT, Panimalar Engineering College, Tamil Nadu, India.
ORCID ID : 0000-0003-4065-2874
6Department of IT, Panimalar Engineering College, Tamil Nadu, India.
ORCID ID : 0000-0003-4065-2874
**Corresponding author: mailtokrish2023@gmail.com*
** Corresponding Author Email: author@email.com*

Smart security features like collision avoidance, traffic sign recognition, lane departure warning, and an instantaneous vehicle accident report are just a few of the notable benefits that autonomous vehicles can provide [3]. Autonomous vehicles can provide entertainment through clever cache in addition to secure driving characteristics. Strong machine-learning Centralized machine learning was employed in several studies to provide various services in self-driving automobiles [5]. Nevertheless, artificial intelligence techniques that utilize centralized learning have a fundamental problem with privacy leaks. Federated learning (FL), which depends on developing international machine learning models without sharing information and only transmits learning variables from smartphones to a centralized computer, was created to address the leakage of privacy problems associated with centralized machine learning [6]. As a result, FL may be used to provide different learning capacities in self-driving automobiles [7]. Conversely, there are situations in which a machine-learning model cannot be trained without constant contact with data-generating equipment. In particular, autos produce 4000 gig octets of information every single day [8]. A centralized machine learning model may not yield satisfactory results after a single training session. FL has some significant issues despite its many characteristics.

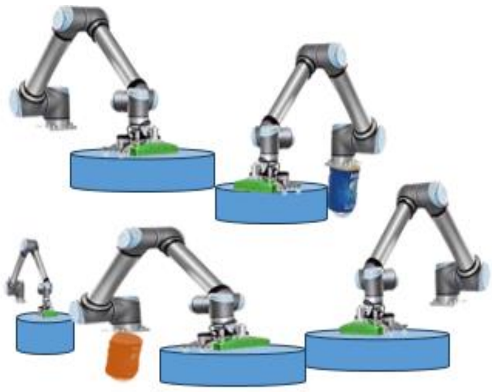
By leveraging the learning modifications, a malevolent end-device or aggregate service might deduce private data about devices [9]. Consequently, it's necessary to guarantee that FL maintains complete confidentiality. In a conventional FL, the local models of learning are aggregated by international servers. If the central aggregating service fails, the process known as FL may be stopped. In conventional FL, devices and a central server communicate often via upgrades. A malevolent entity can assault the central server, changing educational settings and interfering with the learning process. Regular updates between a single server and the devices will necessitate a substantial amount of bandwidth for communication resources, which results in restrictions on the small amount of communication capabilities.



(a)Privacy in data sharing

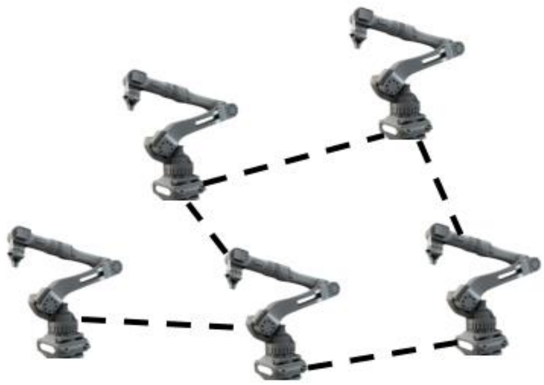


(b) Sharing data collaboratively

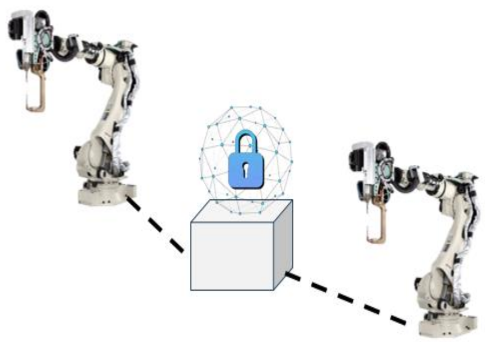


(c)Experiences and environments of Robust learning

(d) Synchronization of cloud system



(e)Networking (Decentralized mesh topology)



(f)Consensus and Connectivity

Fig. 1. Federated Learning and Artificial Intelligence Implementation

At last, each BS sends regional representations to related devices for worldwide aggregate after the entire blockchain consensus system has finished running [11]. Such nodes can immediately communicate algorithms for learning updates with their neighbours over quick back-haul links without the need for a block chain [12].

On the other hand, a hierarchical learning pattern can facilitate resource optimization in the FL process [13]. Nevertheless, since centralized aggregating is used, hierarchy-federated education has a resilience problem. Numerous studies and research articles in the scientific community have examined FL's application opportunities, deployment specifics, and design strategies. In contrast to previous research on safety and confidentiality [14], customized FL [15], or edge communications, this study attempts to give a thorough overview of how FL might be utilized to increase the independence and cognition of robotic devices.

Researchers examine numerous application scenarios for mobile robots that are autonomous and at the edge. Everyone gives a summary of the key ideas and focuses especially on how FL and DLTs might work together because the use of block chain technology has attracted a lot of interest lately [16]. Figure 1 provides an abstract illustration of FL implementations and connection strategies. From local models, it is simple to deduce private data about the final devices (i.e., at the sub-worldwide server). However, a global server finds it very challenging to deduce device data gathered from sub-global revisions to models [17]. The Internet of Vehicles (IoV) becomes an Intelligent Transportation System (ITS) when it is combined with cognitive approaches and enabled by technology for networking [18].

2. Materials and Methods

2.1 Mobile Edge Computing

The methodology known as MEC drives cloud computing services towards the edge of the internet [19]. Real-time use, enormous bandwidth, and extremely low latency are just a few advantages of using the network edge. Video data analysis, services for location, IoV, and augmented realities are a few applications that result from MEC installations [20]. To allow cloud utilization of resources at the connection's edge, MEC itself necessitates virtualizing the architecture of the network.

2.2 Network Function Virtualization (NFV)

NFV are software-based programs that operate on ubiquitous equipment, like edge computers and information center computers, once the network operations have been extracted. Numerous advantages, including decreased investment and operating costs, enhanced network efficiency and achievement, and enhanced networking medical care, may be attained using NFV technologies [21]. NSPs are considering other methods to handle NFV MANO as a result of the increasing level of complexity of networks and the NP-hard computational difficulty of these challenges [22].

2.3 Intelligence and NFV

Regarding NFV MANO functions, the application of intelligence methods like ML and AA has grown in popularity nowadays. However, NSPs may provide accurate system representations without having to fully explain the structure mathematically by modeling the system straight from the produced information [23]. Furthermore, knowledge may be utilized to learn from previous optimum VNF placements and make real-time predictions about future positions in the context of NFV MANO functions or VNF deployment. Because near-optimal heuristic methods are static and optimization issue formulation is difficult, real-time optimum choice-making had previously been unattainable. However, this capacity to forecast optimal arrangements has made this achievable [24].

2.4 Federated Learning on Autonomous Vehicles

FL allows many parties to develop a model together, consisting of neural network variables while reducing privacy hazards. The goal of [25] is to develop a deep neural network model using many customers, or employees, working together with the central server. Different customers may own information with varying volumes and significance levels. A loose federation of clients under the direction of the server underpins FL, which facilitates the effective processing of inaccurate information [26]. By exchanging just the local modifications of the entire model between the main server and customers, FL minimizes the amount of exchanged information. FL may incorporate a lot of user information because of its low overhead for communicating and confidentiality features, which is crucial for building a deep neural network simulation with excellent precision.

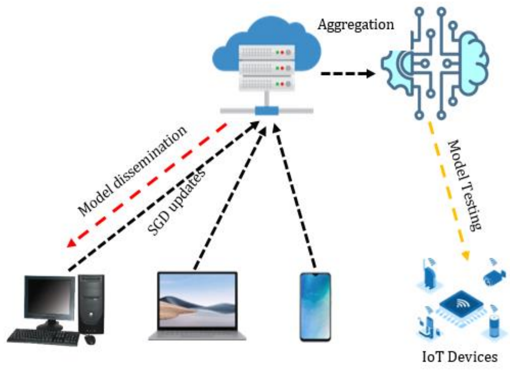


Fig 2: Federated learning

As seen in Fig. 2, FL is a decentralized artificial intelligence technique in which a central server instructs multiple customers (workers) to train a shared model using their personal information. Every customer merely provides an update of the typical worldwide models to the centralized server, which initializes the representation, as opposed to transmitting raw data to the centralized server, as is customary in the conventional centralized learning technique [27]. The centralized server can improve the learning outcome without compromising the confidentiality of the customer's data by employing dispersed training at the client's location. The following are the fundamental FL stages:

1) Consumer choice: The customer nodes that have to be a part of the procedure for training models must be determined by the central server. The model demands for training, customer node characteristics, information dispersion, and other factors should all be taken into account when choosing a customer.

2) Modelling propagation: The first model is sent by the main server to the chosen nodes in the client network with the intent of collaborative learning at these devices once the end-user networks are chosen.

3) Distributed learning: each customer node computes an update to the centralized approach, like SGD for the federation average approach, and trains the model using its local information.

4) Customer feedback: each customer updates the main database on its own.

5) The accumulation: Using a technique (like FedAvg) intended to maximize FL effectiveness, the central server aggregates the changes from the customer nodes to create a new version of the global framework.

6) Model testing: Using information from the remainder of the globe or from organizations that were not involved in the learning process, the main server tests the consolidated worldwide model.

7) Model update: Based on the combined results from all of the customers, the web server modifies the collective framework, which is the representation that will be sent to all of the devices.

Furthermore, two trade-offs were investigated: (a) the device's electrical power and the calculation time of the FL models; and (b) the computation and communications latency according to the learning correctness level. Chen et al. investigated FL over wireless connections in [28]. In particular, the decrease in precision of the global FL model as a result of channel uncertainty was examined. Optimizing transmission strength, customer choice, and allocation of resources were taken into consideration to lower packet mistakes in wireless FL. The researchers established the closed-form formulation of the anticipated FL rate of convergence and gave an in-depth examination of PER on the wireless FL reliability. The optimization issue is formulated in a closed-form express structure, and the Hungarian method is used to solve it. The writers also talked about how difficult it would be for them to carry out their suggested plan. To minimize the loss operation, a control method with resource budget restrictions was put forth that provides a tradeoff between local updating and worldwide variable aggregate. Through simulation outcomes and prototype deployment, their approach was validated on an actual database [29].

3. The Contests of Machine Learning Implementation in Its

The application of ML in extremely dynamic situations like IoV and ITS presents several obstacles. These difficulties may be divided into four main categories: handling information, performance of models, confidentiality, and complexity of systems [33]. Since the atmosphere around wayside infrastructures is very variable and VCs are constantly entering and exiting the framework, the complexity of the system is a significant barrier to evaluating ITS shown in Fig. 4.. The operational domain is constantly changing due to this volatility, implementing machine learning (ML) presents a special difficulty that typical ML cannot readily manage [34]. The performance of the model is the second significant difficulty that arises from the altered operational area. The effectiveness of the model is negatively affected by changes in the operational domain. Static neighborhood intelligence models suffer from substantial decreases in efficiency and are unable to adjust to fluctuating contexts.

Preserving human life is of utmost importance when thinking about the vital nature of an ITS. The safety of the population might be at risk from any degree of systemic breach, including those affecting its data and infrastructure. Ultimately, data administration becomes more and more important as the number of network nodes with processing capacity increases. Given the restricted resources available for the wayside infrastructure, particular attention needs to be given to the efficient storage of information [35]. The roadside infrastructure's limited resource capabilities make it impossible to store huge amounts of information, which might lead to inadequate information during the conditioning phase of standard localized machine learning approaches.

3.1 Why do Vehicles Need AI

The need for smart vehicles is growing quickly due to economic growth. Nearly every nation is dealing with serious issues related to road safety, pollution in the environment, and congestion, in addition to the steady and rapid rise in vehicle ownership. Meanwhile, the annual count of deadly road accidents is rising, with mistakes made by people accounting for the majority of these incidents [36].

It is anticipated that the number of fatal traffic incidents will increase as automobile ownership continues to rise. By utilizing cutting-edge AI methods, we can resolve the above-described issues. The four primary issues that render automobiles urgently in need of AI approaches are summarized in Fig 5.

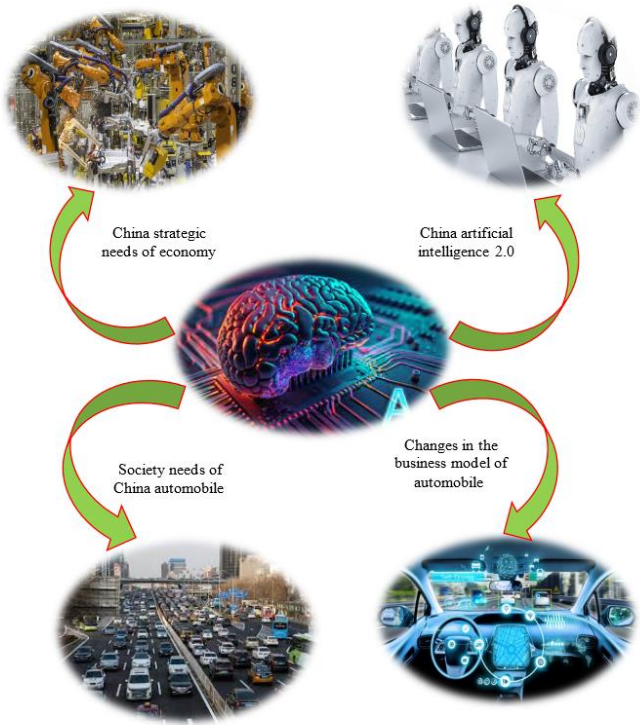


Fig. 5: AI main factors in autonomous vehicle driving

3.2 Next-Generation AIV

The next generation of AIV is expected to have more standardization and flexible AI features because of the quick advancement of AI methods and vehicle-related technology. The proposed AIV framework for the next generation is depicted in Fig 6. AIVs will be implemented in certain application situations, and their associated AI functions will be well-defined during the next ten to twenty years. The three components of AI functions are world models, planners and administrators, and platforms for computing. Creating a high-precision map is essential to implementing a visual autonomous positioning technology at fast speeds [37].

An intelligent automobile has improved actuators, controllers, and vehicle sensors, among other features. Additionally, there is a new breed of intelligent cars that combine contemporary communication and network technology to provide sophisticated environmental issue perception, astute decision-making, and management capabilities. These features can be combined to provide energy efficiency, preservation of the environment, and comfortable driving [38-40]. Through particular devices that may fuse car connections to realize car interactions, internal connectivity, and automobile roadway interaction (car connection with system centers, smart transportation systems, and other service centers), the automobile can realize intra- and intra vehicle interaction in addition to communicating with highway traffic. Fig. 7 illustrates the essential components of AI in connected automobiles.

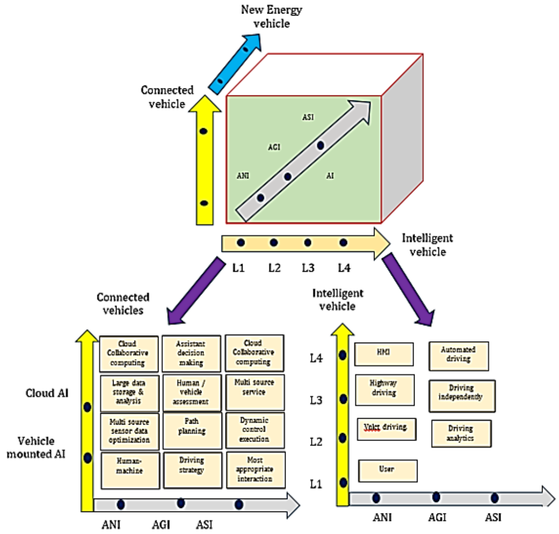


Fig 6. Integration of vehicle using AI

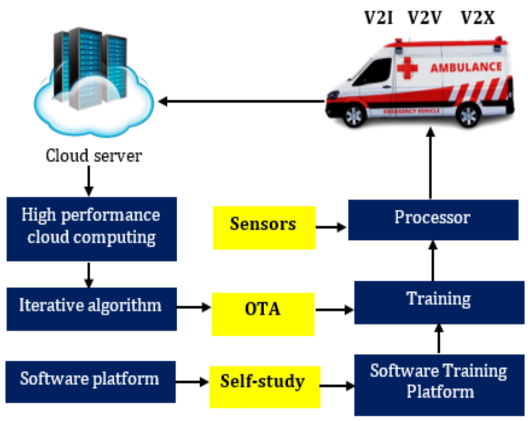


Fig 7. Key factors used for digital and intelligence

4. Research Gap

Enhancing automated transport through the combination of federation learning and machine learning offers a viable approach to improving the effectiveness, security, and flexibility of public transport systems. Moreover, several research gaps exist in this area that warrant further investigation. While federated learning enables collaborative model training across distributed devices, ensuring scalability and efficiency in large-scale autonomous transport systems remains a challenge. Research is needed to develop scalable federated learning frameworks tailored specifically for the complexities of autonomous transport environments. Federated learning relies on decentralized data processing to preserve data privacy, but ensuring robust privacy and security protections in autonomous transport systems is crucial. Research should focus on developing advanced encryption and authentication mechanisms to safeguard sensitive data shared among vehicles and infrastructure components. Autonomous transport ecosystems comprise diverse vehicles, sensors, and communication protocols, leading to heterogeneity and interoperability challenges. Future research should explore methods to facilitate the seamless integration of federated learning models across heterogeneous devices and platforms while ensuring compatibility and interoperability. Autonomous transport systems operate in dynamic and uncertain environments, requiring adaptive learning mechanisms to respond effectively to changing conditions. Research is needed to develop federated learning algorithms capable of dynamically adapting to varying environmental conditions, traffic patterns, and infrastructure changes in real time. To reduce latency along with information movement, federated education frequently uses devices at the edge for training models. However, optimizing model training and inference processes on resource-constrained edge devices in autonomous transport settings remains an open research challenge. Future studies should focus on developing efficient edge computing strategies tailored for federated learning in autonomous transport.

As autonomous transport systems become more prevalent, addressing regulatory and ethical considerations surrounding federated learning and AI integration is essential. Research should explore frameworks for regulatory compliance, accountability, and ethical guidelines governing the use of federated learning in autonomous transport, including data ownership, liability, and transparency. Autonomous transport systems must be robust and resilient to adversarial attacks, sensor failures, and unexpected events. Approaches for strengthening the federated learning models' resistance to adversary assaults, information ingestion, and other safety hazards in driverless transportation contexts should be the subject of additional studies. Addressing these research gaps will not only advance the field of autonomous transport but also contribute to the development of safe, efficient, and trustworthy transportation systems enabled by federated learning and artificial intelligence integration.

5. Conclusions

In conclusion, the integration of federated learning and artificial intelligence holds significant promise for enhancing autonomous transport systems in various aspects such as efficiency, safety, and adaptability. This innovative approach leverages decentralized data processing, collaborative model training, and adaptive learning mechanisms to address the complexities of autonomous transport environments. Autonomous vehicles may learn from dispersed sources of information while maintaining confidentiality and safety, thanks to this connectivity. Thereby enabling scalable and efficient model training across heterogeneous devices and platforms. Moreover, federated learning facilitates real-time adaptation to dynamic environmental conditions and infrastructure changes, ensuring robustness and resilience in autonomous transport systems. However, several research gaps exist that warrant further investigation, including scalability and efficiency, privacy and security, heterogeneity and interoperability, dynamic environment adaptation, edge computing optimization, regulatory and ethical considerations, and robustness and resilience. Addressing these research gaps will not only advance the field of autonomous transport but also contribute to the development of safe, efficient, and trustworthy transportation systems enabled by federated learning and artificial intelligence integration. With continued research and innovation, autonomous transport systems powered by federated learning and AI integration have the potential to revolutionize the way we commute, transport goods, and navigate urban environments in the future.

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Author contributions

Y.Pradeep Kumar and V. Mustafa: Conceptualization, Methodology, Software, Field study **G. Sudhakar and Kavin Francisxavier :** Data curation, Writing-Original draft preparation, Software, Validation., Field study **Rajeshwari V and Krishnaraj M:** Visualization, Investigation, Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

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