Decision-support system for smart cities to assess and manage terrorist threats

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Society and terrorism

The dimensions and characteristics of international terrorism are dependent on historical and geographical context, political links, or various factors related to specific terrorist groups and organizations. The social and economic impact it generates means counterterrorist security has become one of the greatest challenges for law enforcement agencies, policy makers, and institutions.

Despite this dependence on differing factors, terrorist attacks are generally intended to cause great harm and create consternation in the population. Urban public spaces are key targets for terrorists because large populations cluster vulnerably in these areas.

The field of urban counterterrorist security for the defence of critical infrastructure and soft targets, more specifically in the context of mass events, has made adequate planning and the preparation of emergency response strategies mandatory. In 2021, the Global Terrorism Database (GTD) recorded that more than half of the attacks worldwide make use of Improvised Explosive Devices, mass shootings, and arson or incendiary/smoke device attacks. Projecting the evolution of these types of attacks is necessary to develop models to help minimize their consequences.

In addition, 29.4% of the terrorist attacks between 2010 and 2020, were directed against the general population [16] meaning that cities are becoming a significantly important target for terrorists. This paper therefore proposes a decision support system for emergency management that can be used during planning and response to anticipate terrorist threats to help address these issues.

Smart cities as a countermeasure

Smart cities that use current information and communication technologies to increase operational efficiency, share useful information with the population, and improve the security of government services, can be a tool to ensure citizen welfare.

It is mandatory for smart cities to create a safe physical and digital ecosystem for their inhabitants. To this end, it is crucial to fully use all the capabilities already available for enhancing safety and security. These include, for example, anomaly detection, identification and authentication of individuals, threat localization, behavioural profiling, suspect tracking, traffic monitoring, emergency management, and many other capabilities related to awareness, prevention, and response [22].

These capabilities have been studied from different perspectives leading to a wide range of results including the detection of individuals and threats [5], [9]; detection and tracking [2], [8]; recognition-based authentication [4], [7]; or the enhancement of legacy systems deployed by the city by equipping them with intelligence [37], [38].

However, it should be noted that there are hardly any studies [6], [12], proposing the use of a comprehensive decision support system that simultaneously includes emergency management; forecasting the evolution of threats and the impact of the most common terrorist attacks; and real-time decision support. The closest studies in the existing literature focus on the management of common crimes such as vandalism and violence [15], information systems [32], the management of abnormal traffic [17], emergency evacuations [36], and, to a lesser extent, on the prediction of events such as robberies or murders [3], [26]. Consequently, we contend that it is necessary to simultaneously forecast and assess the impact of the most common terrorist attacks, while at the same time managing emergency situations regarding pedestrians and vehicles, evacuations and surveillance, by making use of comprehensive conceptual and computational models to support decision-making.

Theoretical framework for terrorist threat assessment and management

In order to improve terrorist threat assessment and management in smart cities by exploiting smart-city features, we have proposed a theoretical framework based on the initial definition and capabilities of a smart city using a three-layered structure to formalize the proposed model (see Fig. 1).

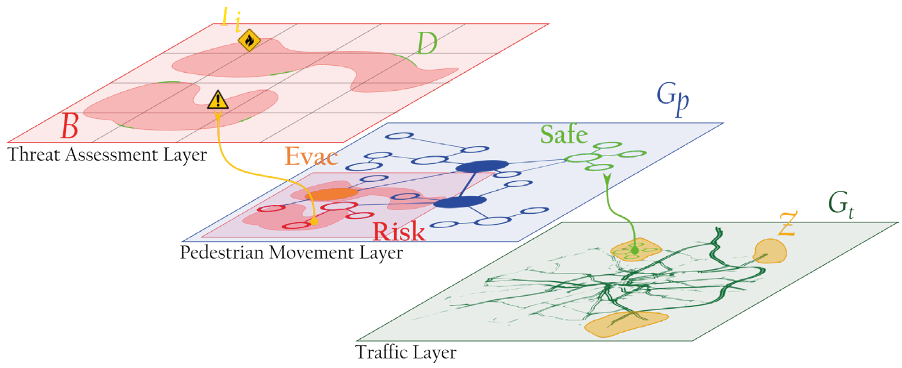

Fig. 1. Layer-based theoretical framework for terrorist threat assessment and management applied to a hypothetical Smart City.

Threat assessment layer

This comprises a set of soft targets such as crowded areas and infrastructure where security monitoring is desirable. (A soft target can be defined as a geographically delimited and bounded area, taking into account its safe zones and obstacles, which is associated with a spatial distribution of people and deployed security devices such as checkpoints, cameras, or patrols. Therefore, the threats monitored in these zones are defined as sets of locations and categories, for example fire, smoke device, explosive device, or firearm.) This layer assesses the threats and potential impacts/consequences of three types of attacks by generating results summarized as a set of geographic locations linked to counter-terrorism security information that allows lower layers to increase their level of intelligence to enable more accurate modelling results.

1. Arson and smoke bomb: A fire dynamics simulator [24] is used for the most likely locations of these types of attacks by simulating various scenarios in which the actual combustion parameters (different loads of wind and fire) are changed. The results generated provide artificial measurements such as visibility and fractional effective dose that are then classified and stored in a structured way for later use.
2. Improvised explosive device (IED): based on a threat probability approach [10] this layer divides the geographic area of the simulated scenario into small regions that conform to a fine grid of square cells. A risk function is calculated for each cell within the grid based on factors such as distance to exits, population density and distribution, or distances to deployed resources. After processing all cells, a matrix of risk values is obtained and combined with the threat level, resulting in a probability map with critical locations for each soft target.
3. Mass shooting attack (MSA): An agent-based model that discretizes the scenario being studied by means of uniformly distributed reference points. These are subsequently displayed as nodes on a direct reachability graph for the purposes of calculating the agent's trajectory. The optimal trajectory from each initial location is calculated using a backtracking approach with the associated cost function based on three key factors: 1) the proximity of a node to an exit/security zone; 2) the spatial availability of that node; and 3) the risk associated with the attacker's location. After these routes have been calculated, the movement and behaviour of the people involved in the scenario are represented using a microsimulation approach that considers the interactions of agents and the repulsive forces between terrorists, people, and the scenario boundaries and obstacles through a social force model [18]. To represent people who are shot, we follow an approach based on the physical dynamics of gunfire [1], in which the probability of being shot is estimated and the number of victims is calculated using a stochastic approach.

Pedestrian movement mayer

The topological definition of traversable pedestrian zones is replicated in the form of a graph in which each node is defined by its geographic location and occupant density, as well as by its current status (passable, impassable, evacuated, safe). Similarly, each boundary represents passable zones and is defined by its people density, origin and destination nodes, and available flow. Using the threat assessment layer results as input for the pedestrian movement layer, the status of each node in the network can be updated, indicating safe nodes; affected impassable nodes; and assigning nodes to be evacuated. In addition, the occupancy densities of the different nodes and boundaries of the network are updated using one of the following approaches, depending on the capabilities of the smart city: 1) estimates based on the history of predicted occupancy; 2) real-time monitoring of occupancy via cameras, Wi-Fi tracking devices, access controls or similar; and 3) random assumptions of occupancy based on predicted distributions.

This graph is used as a reference graph to perform an initial calculation of minimum paths using Dijkstra's algorithm. Its subsequent optimization is performed by considering node availability and using a weighted multiple criteria decision analysis (MCDA) to evaluate conflicting nodes. The MCDA considers the weights associated with the different criteria by defining a function that produces an unweighted, normalized relevant score for each criterion and inverts it to maximize it where necessary. The weights are calibrated for each network using defined scenarios to ensure that the ranking of results is logical, and to improve the efficiency of the optimization model. The criteria considered are: congestion and additional distance cost incurred by re-routing different nodes; and congestion and available flow at surrounding nodes. Then, following an iterative process, we generate a set of candidate networks that resolve these conflicts and apply another MCDA scoring function among them in the same way to choose the optimal network. In this case the criteria considered are the estimated total evacuation time and the sum of the node congestion in the candidate network.

Once the optimal graph is found it becomes the active graph and can be iteratively optimized as model inputs change. This model provides evacuation routes, estimated departure times, and mobility profiles and forecasts the number of people who will go to specific locations in a specific time period by determining and modelling the initial impact on the traffic network.

- Traffic layer: This layer provides a real-time traffic forecast on the different sections of road by date and time following a network calibration based either on historical traffic data or data obtained from traffic monitoring sensors installed in the smart city. Similarly, to the pedestrian layer, the traffic network is also represented by a graph in which the vertices represent vehicular traffic landmarks associated with physical locations and the axes represent the reachability associations similar to the pedestrian layer but with density and flow measurements for vehicles instead of people. To generate traffic profiles, this layer considers the different habitual areas of trip origin and destination, which in turn are related by proximity to a node of the traffic network, generating a set of routes and a weighted origin-destination matrix. The calibration process starts from the non-calibrated network represented by the graph that solves the shortest routes considering the availability constraints of the sections of road and updates the origin-destination matrix using route-based algorithms [19] and bush-bashed B [13]. Thereafter, following an iterative process to adapt the origin-destination matrix based on the gradient approach [31] with some adjustments for large traffic models [21], the model optimizes the set of trajectories and the origin-destination matrix based on real traffic data, paying attention to discrepancies between the model and reality. The applied methodologies can, therefore, be summarized in two models for specific purposes.
- Trip distribution model: the classical gravity model is used for the trip distribution model. The distribution model estimates the number of trips between two zones by considering the number of trips originating from the source zone to the destination zone and the equilibrium coefficients that are determined by the iterative proportional adjustment procedure. The most important part of this distribution process lies in the deterrence function that considers the cost (travel time) between the zones. The forms of the deterrence function are described in [28].
- The traffic assignment model is used to address the traffic assignment problem (TAP). The definition of TAP is based on Wardrop's first principle. This principle states that for all paths used from the source node to the destination node the travel time must be equal, and this travel time must be minimal [35]. All pairs must fulfil this condition. Mathematically, TAP can be defined as a variational inequality (VI) per [30] and [11] where the set of feasible flows associated with the origin-destination matrix is considered. To solve this problem, Jayakrishnan's trajectory-based algorithm [19] is combined with Dial's bush-based algorithm B [13] with certain improvements by Nie [25] and the fully parallelized implementation of algorithm B [29]. Algorithm B decomposes the problem into bushes. A bush is the acyclic subgraph of the main graph relating to the source area. A bush contains only the flow from the source zone to all other target zones. Each bush is balanced by shifting the flow from the minimum path to the maximum path. The minimum and maximum paths are topologically ordered in the acyclic bushing. In terms of the source-destination matrix calibration algorithm, the Spiess method [31] is implemented with some adjustments. This method uses the steepest descent with a long step to minimize the object function. Some adjustments are described in [21].

From theory to practice

To test this theoretical framework, a decision support system was implemented according to the architecture presented in Fig. 2 to help security managers in the planning and response phases by taking advantage of some of the resources and devices already installed in smart cities. Examples of these resources and devices include cameras, Wi-Fi monitoring devices, access control sensors, and so on. These devices can help estimate the number of people in specific locations while, for example, traffic monitoring systems make real-time simulation of abnormal traffic flows more reliable.

The architecture follows a producer-consumer approach using a centralized platform of distributed data flows (Apache Kafka)

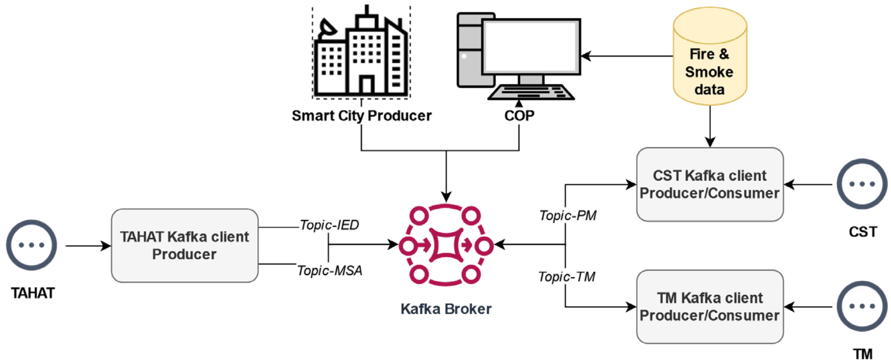

Fig. 2. Overview diagram of architecture. Terrorist attack hazard analysis toolkit (TAHAT), crowd simulation toolkit (CST) and traffic modeller (TM) modules.

Fig. 3. Diagram of the Doosan Arena drill case study. 1) Doosan Arena stadium (green); 2) Boundary of drill area (yellow); 3) Car parks near drill area (blue); and Drill location (red).

to exchange information between layers. In turn, each layer is implemented as an independent module with a graphical user interface (GUI) for configuration and an application programming interface (API) that provides an on-demand service to the rest of the layers, except for fire and smoke simulations that have to be pre-simulated due to the computational cost and then stored locally for later use in specific scenarios, if necessary. Various development technologies were used to implement the individual modules, the main ones being:

- Microsoft .NET Framework 4.6.1: calculation of the terrorist attack simulation and scenario management using the Mapsui, BruTile and SkiaSharp libraries.
- Fire dynamics simulator: ad-hoc modelling of critical soft targets and fire-risk infrastructure.
- Unity: creation of the pedestrian evacuation network with respect to real landmarks, providing geospatial references.

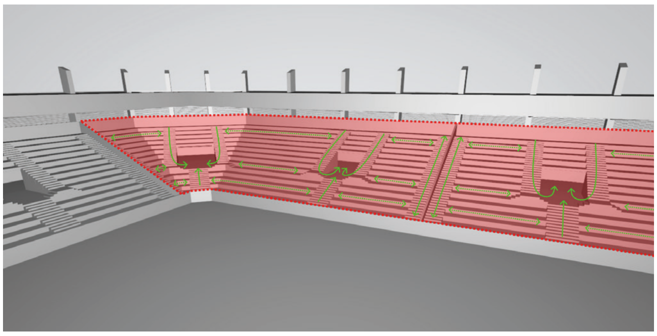

Fig. 4. 3D model of the stadium interiors showing the drill area, with drill boundaries and available evacuation routes.

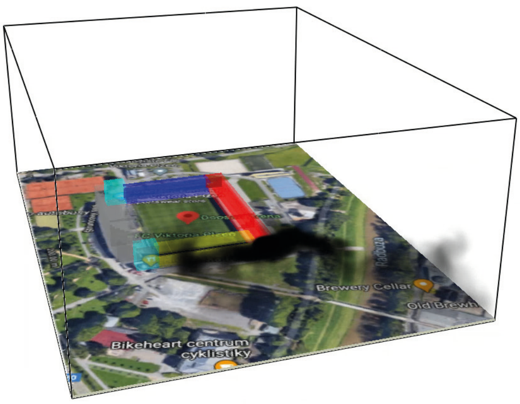

Fig. 5. Smoke propagation in the GUI of the fire dynamics simulator (FDS) simulation.

- HSlayer framework: implementation of traffic layer elements including geographical information systems (GIS) functionalities.
- Apache Kafka: information exchange between modules.

Once a usable implementation became available, the system had to be validated by means of a case study. The case study was designed using data provided by Správa Informačnich Technologii Města Plzně, p.o., a partner in the S4AllCities project.

It was tested in a terrorist attack drill that took place in the Doosan Arena stadium in the city of Pilsen in the Czech Republic and was organized and conducted by the Czech police (see Figs. 3 and 4). A detailed description of the stadium and its surroundings, along with the city of Pilsen itself and the chronology of the drill were provided, including information such as:

- A 3D model of the Doosan Arena obtained by Lidar and RGB scanning using DJI Zenmuse L1 and DJI Zenmuse P1 cameras.
- Initial locations and specifications of a possible smoke bomb (Antari Z 3000 II fog machine).
- One year of traffic data providing a dataset of 250 million observations from 627 sensors embedded in the road, with a 90-second time granularity traffic model calibrated from traffic data [20].
- A 2D map of the areas surrounding the stadium with the expected attendance (11,700 spectators + 3,300 people), transit locations, typically deployed security resources, car parks, and other minor details.

Regarding the structure of the drill, several exercises were conducted combining explosive devices with firearms (pistol and rifle) and a variable number of shooters (1-2). Each iteration was organized in three rounds: 1) placement in the grandstands of volunteers acting as victims (600 people); 2) initiation of the mock attack; and 3) police intervention and evacuation. In this last phase the system was activated to provide information to first responders on the potential number of victims and dangerous areas and, in the case of an incendiary or explosive device, the spread and impact of the resulting fire. The current status of the evacuation process and anticipated developments are also provided, tother with the projected abnormal traffic flows and their impact on the city's traffic network.

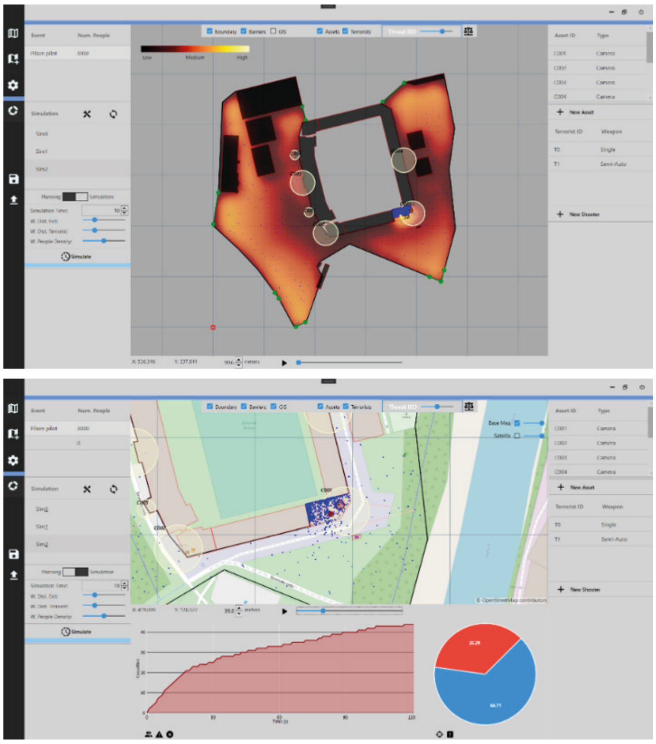

Fig. 6. Simulation results presented via GUIs for threat assessment and impact analysis of IEDs and MSAs.

Fig. 7. Pedestrian evacuation management GUI showing agents leaving the stadium and heading towards car parks across the city.

It should be noted that the scope of the simulations is not limited only to the simulation area presented in Fig. 5. Instead almost the entire city centre is included in the evacuation and traffic simulations, as can be seen in Fig. 7. and Fig. 10.
The results of the on-site implementation and the real-time operation of the system are provided sequentially according to the details and structure of the drill and following the logical course of the emergency event.

Fig. 8. Crowd density levels on routes surrounding the stadium (top) and the first responders route (red line) towards stadium (bottom).

As mentioned previously, the case of the "smoke bomb" explosive device combined with a mass shooting attack was simulated using a sound effect and smoke machine located below the grandstands for the bomb, together with two volunteers acting as shooters who were located at the top of the grandstands. For this case, the system provided various types of results, starting with the retrieval of the output of the FDS analysis of the smoke propagation (virtual smoke machine set on the Antari Z 3000 II fog machine, wind direction NW); followed by the simulation of the impact of the threat and the attack where the system operator is shown both the evolution of the different incidents and the data associated with the artificial scenario measurements (probability of IED, fractional effective dose (FED), visibility, and casualties). As can be seen in Figs. 5 and 6, the results present the visible spread of the smoke and the potential IED firing positions by means of a probability heat map. These results also reveal that, in the real event of such an attack a total number of 44 casualties could be assumed in a worst-case scenario, considering an attack perpetrated by two shooters and assuming it takes two minutes for the intervention forces to reach the emergency site.

After this initial phase of the attack, the evacuation phase would begin sequentially and automatically due to the panic created. For this case, using the complete model from the stadium to the car parks to simulate the evacuation of the stadium and surrounding areas to the car parks would normally take 58 minutes of simulation time, but the proposed

Fig. 9. GIS data representing the traffic network, car parks, and drill area to be unified with pedestrian evacuation.

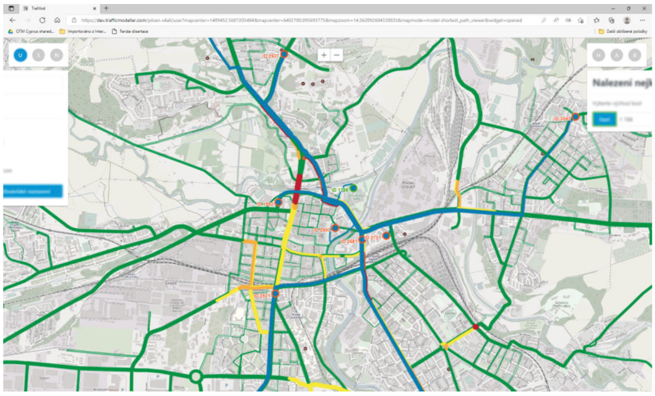

Fig. 10. Traffic network status simulation GUI showing abnormal traffic.

solution completed it in only a few seconds of real time. The simulation was followed by an evacuation of 600 volunteers who followed the routes suggested by the model; they were able to evacuate the stadium grandstand in eight minutes.
The crowd simulation component was used in several ways during the Pilsen scenario. A small-scale simulation of 600 agents was conducted to represent the same conditions as the simulation undertaken in the field, in which the 600 volunteers were able to follow the routes to exit the stadium grandstands sent by the component. An evacuation of the entire stadium was also simulated to demonstrate the component's ability to simulate large-scale models. In both scenarios, the density of evacuating crowds was calculated with the Fruin level-of-service scale, which calculates the density of crowds as they leave the stadium and disperse across the city by assigning a colour scale based on the concentration of people per square meter per minute. The component integrates with the traffic modelling component by considering the results of the traffic model and the expected waits at intersections and road junctions, and then provides input to the traffic model regarding arrival patterns at the car parks surrounding the stadium.

Thereafter, the intervention phase would be initiated by the arrival on the scene of the intervention methods during which the evacuation model provides the principal safe-access routes to the incident site, considering the progression of the threats. The systems allow both incidents and the evolving crowd situation, including the concentrations of people evacuating the stadium, to be defined or modified manually (see Fig. 8). In all cases, the component is able to simulate faster than real time and provide safe and optimized routes in a very short time. The component runs continuously in the background, allowing the system operator to request the most up-to-date evacuation or first aid routes as they are needed, and allowing these to be disseminated to those on the ground for the most effective response to an incident.

The last simulation given by the system according to the logical evolution of the event would be the emergency's impact on the traffic network of the city of Pilsen (see Fig. 9). Based on the pedestrian evacuation data of the large-scale scenario that considered the full stadium, the impact of abnormal vehicle traffic flows on the city's traffic network was simulated. The number of spectators and the time of their arrival at their respective vehicles were taken from the results of the previous simulation (the spectators' evacuation from the stadium). Vehicles were directed by the traffic model to specific streets in Pilsen, and this traffic was added to the normal traffic. Congested intersections that could be controlled by the crisis scenarios were identified. Concurrently, the fastest routes for the vehicles of the integrated rescue system were identified. These pedestrian evacuation profiles would increase the traffic in the first hour by approximately 700 vehicles in the northern traffic section and 900 vehicles in the southern section, creating a high density of vehicles in both directions, as shown in Fig. 10.

How we got here and what lies ahead

Emerging technologies being used in smart cities, together with innovative computer simulation tools and methodologies being applied to threat analysis and citizen security represent a breakthrough in the fight against terrorism. This paper described the design of a methodological framework with three layers (threat, pedestrians, and traffic) and the implementation of a decision support system to enable private operators, law enforcement agencies, and local authorities to effectively protect soft targets in a smart city. This system provides support for both threat assessment and emergency management of pedestrian evacuation emergencies and their impact on the metropolitan traffic network. This paper also presented a case study based on data from a simulation exercise in the city of Pilsen in the Czech Republic, where the system was installed and the correct functioning of the different layers of the system was evaluated in situ during the simulation exercise. This case study better illustrated the advantages and features of the implemented system, including its analysis of the main terrorist threats; the comprehensive management of evacuations; and monitoring for decision making regarding the state of the traffic network.

The limitations of the proposed system can be resolved in subsequent developments. For one thing the system does not cover all types of dangers within a city and scenarios should be defined in advance so that data for calibration and modelling purposes can be obtained. More specifically, current reports [14] suggest that future trends in terrorism will evolve towards low cost attacks (knife attacks or ramming with vehicles), or combined attacks (cascading attacks or sabotage of critical infrastructure). On the other hand one of the benefits of this theoretical framework is that it can be applied to other fields. For instance, the possible direct interaction of terrorist threats with the traffic network can be explored, which could lead to the development of riot control measures during urban planning, among many other fields of application. In our view, these limitations are not obstacles but open up future lines of research that will lead to the development of ever more comprehensive safety and security systems.

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