

# **UK's National Edge AI Hub**

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## **Problem statement (socio-economic)**



Within the UKRI funding portfolio, ours is the only Centre of Excellence dedicated to overcoming the key <u>Socio-Economic</u> <u>Question</u>: How UK companies can use edgeAI in a safe and secure way?

Lack of critical workforce having technical skills in edgeAl [UK Government (2022)]



Source: UK Government

Source: Fortune Business Insights

#### The Emergence of Edge Al A Game changer for Industries (Gartner 2023)



Edge AI will be the <u>nucleus</u> of AI Innovation over the next 10 years (Gartner 2023)

## >55 Industry Partners

Supported by 55 organisations in 7 sectors, including 20 new partners after submission.





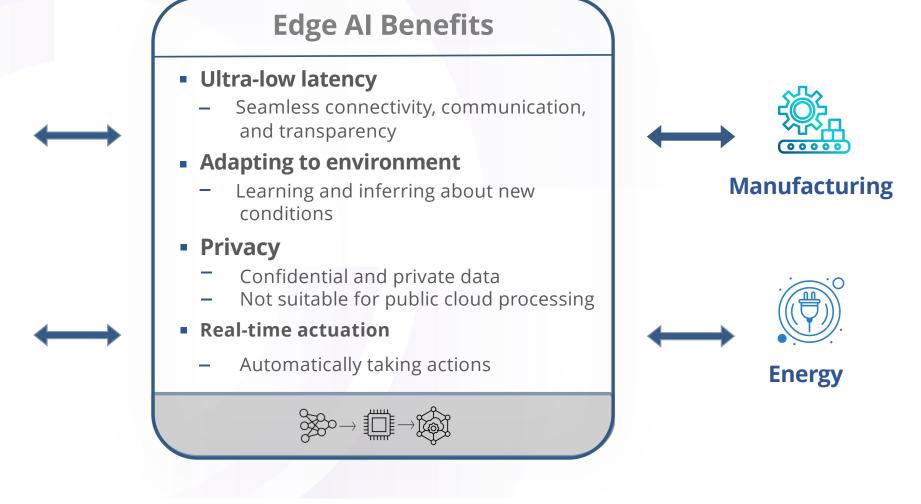
## Problem motivation (Why Edge AI?)



Smart Transport



Healthcare



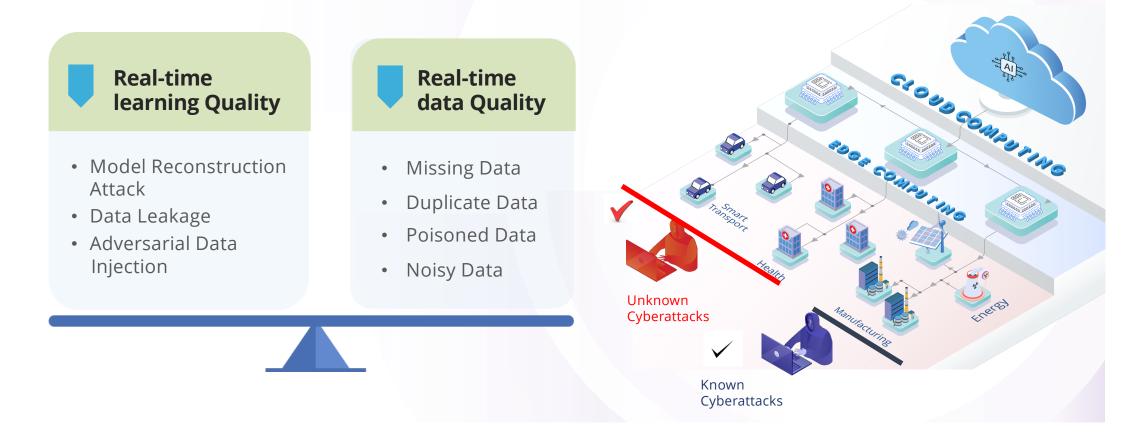
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## **Problem statement (Cyber-disturbances & Edge AI)**

<u>Ground-breaking Unsolved Research Question: How to ensure the Safety and Security of AI and Data from known</u> and unknown "Cyber-Disturbances" at the Edge in Real-time?



## **Hub Vision**

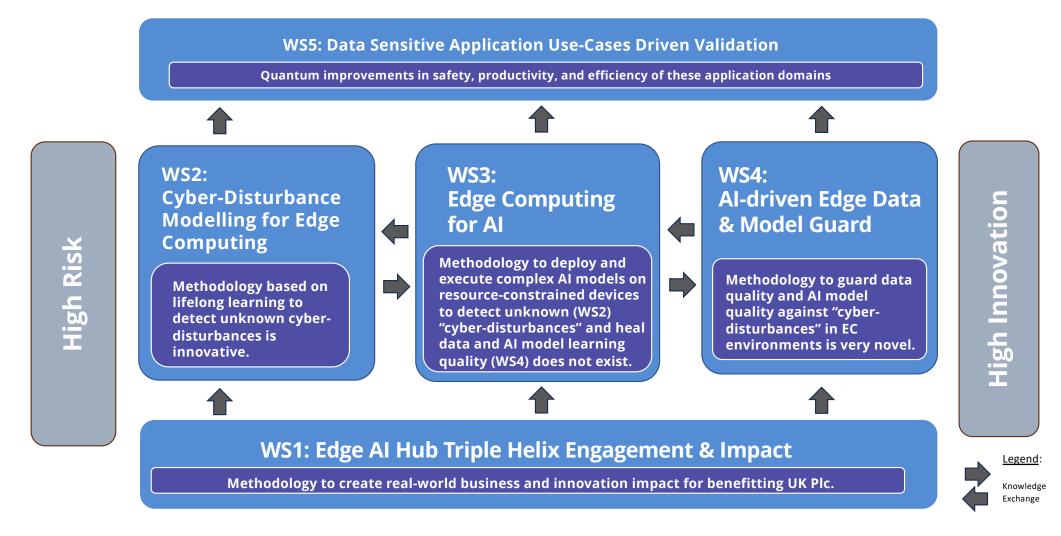
To deliver world-class fundamental research, co-created with stakeholders from other disciplines and regions, to protect the <u>quality of data and quality</u> of learning associated with AI algorithms when they are subjected to <u>known and unknown cyber-</u> <u>disturbances</u> in the EC environments





## High Risk/High Gain Innovation through Workstreams

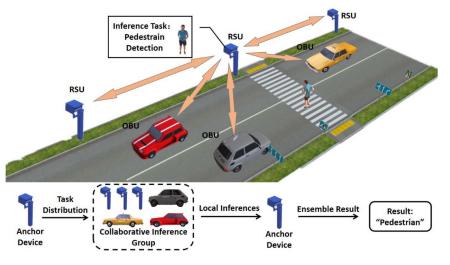


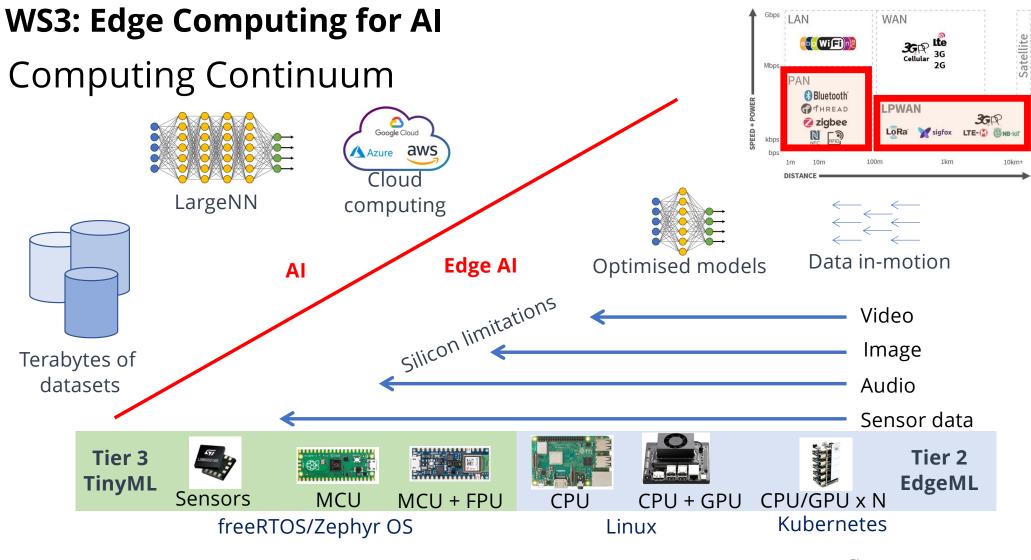


## WS2: Cyber-Disturbance Modelling

- Cyber-Disturbance Impact on Age of Data
  - Investigating how various cyber-disturbances affect the integrity and reliability of data in edgeAI systems.
- Towards Secure AI :
  - Improve fundamental understandings of how to secure AI: generative AI, and specific attacks (e.g. model inversion), inference-time security measures and classification-time security measures.
- Knowledge Graphs for Cyber-Disturbance Modelling:
  - Developing knowledge graphs that can effectively represent and analyse the complex relationships between cyber-disturbances and their attributes.







National Edge Al Hub

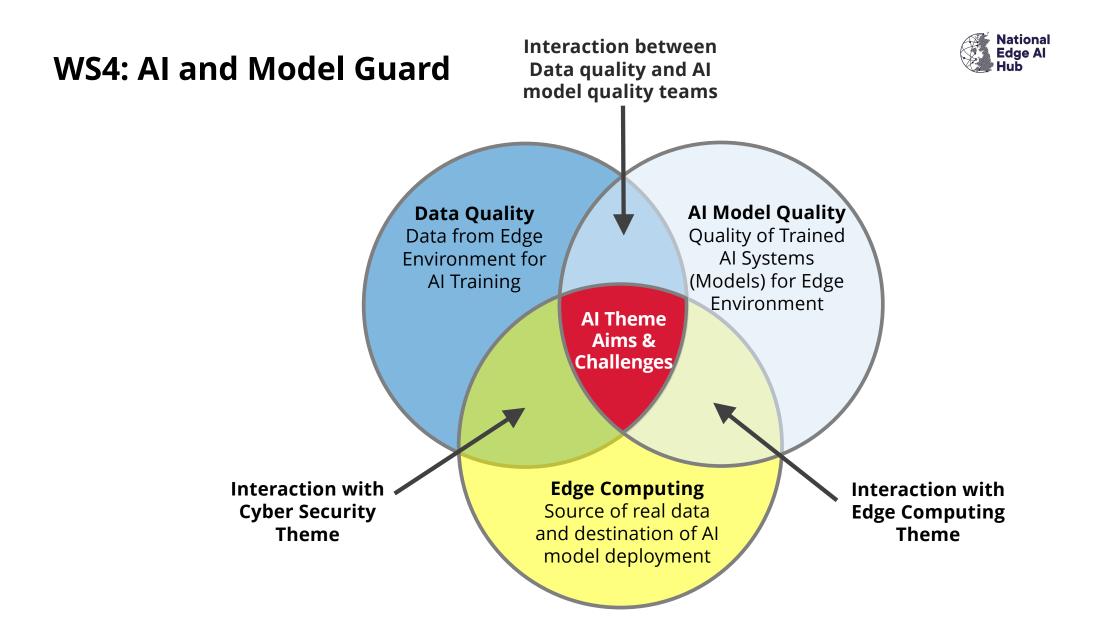


# WS3: Edge Computing for AI

- Edge Computing systems are complex and can be very different from each other
  - Limited resources, hardware heterogeneity, several ML tools and techniques, intermittent communication, etc.
  - Makes it hard to deploy ML models to work well
- Aims to simplify training and deployment of complex Edge ML models

Execution of Edge ML models on different types and families of resources Adaptation of Edge ML models to operational changes and failures in the end-to-end IoT system

Create new tools and techniques that help practitioners achieve the above



# Federated Learning (all WSes): Alignment with Federated Compute Services NetworkPlus

#### **Main Types of Federated Learning**

#### **Horizontal Federated Learning (HFL)**

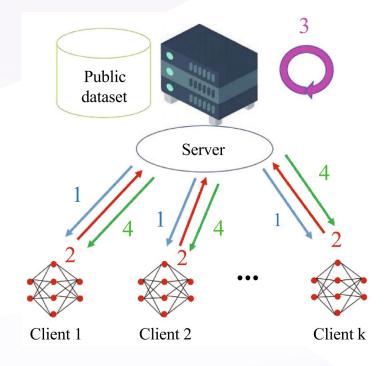
Example: Multiple banks can collaboratively train a credit scoring model without sharing customer information.

• all participants have data with the same features (e.g., different banks with similar customer transaction data)

#### **Vertical Federated Learning (VFL)**

Examples: A bank and an e-commerce platform can jointly train a model, with the bank providing users' financial data and the e-commerce platform providing shopping records to predict credit risk.

• <u>a</u>ll participants have data with different features (e.g., a bank with customer credit history and their shopping records)



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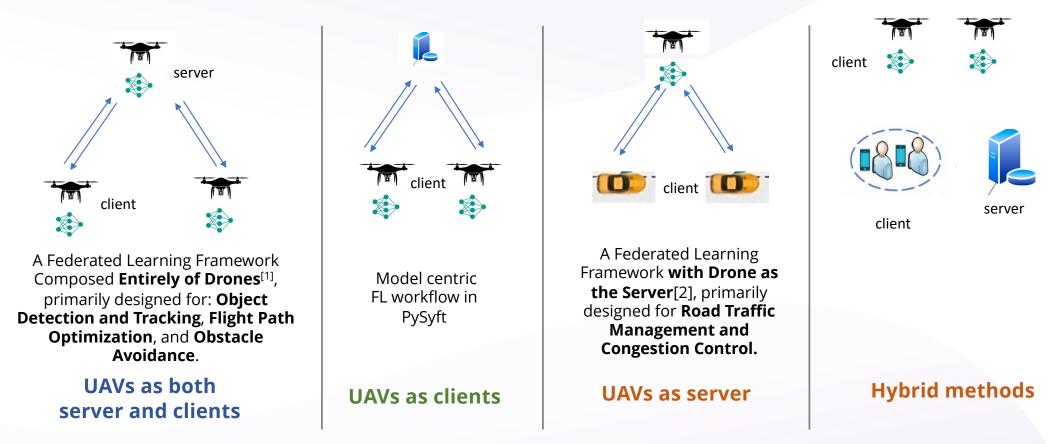
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A schematic of federated learning. It includes four steps: 1: The central server sending the initialized global model to the client. 2: The clients then train locally and submit the local updates to the server. 3: The server performs the model aggregation. 4: the server sends the aggregated model to the clients<sup>[1]</sup>

[1]. Feng, Yunhao, et al. "A survey of security threats in federated learning." Complex & Intelligent Systems 11.2 (2025): 1-26.

# **Federated Learning in UAVs**





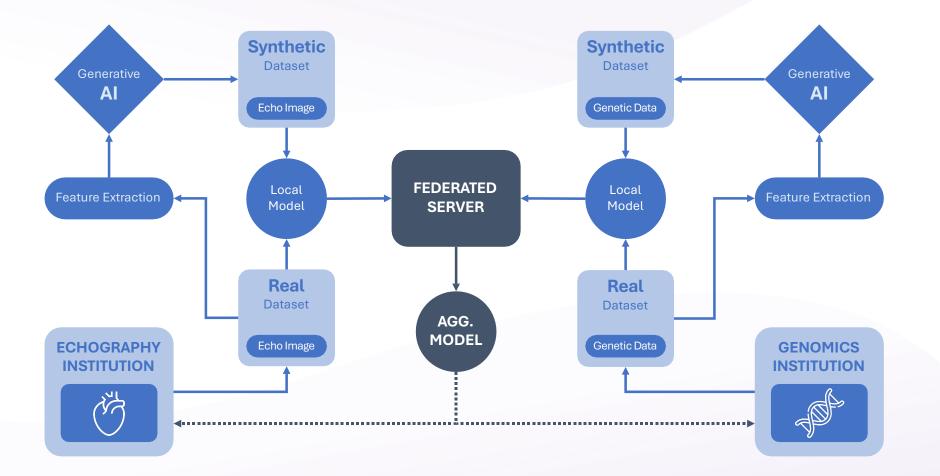
[1]. Yazdinejad A, Parizi R M, Dehghantanha A, et al. Federated learning for drone authentication[J]. Ad Hoc Networks, 2021, 120: 102574.

[2]. AI Farsi A S, Khan A, Mughal M R, et al. Privacy and Security Challenges in Federated Learning for UAV Systems: A Comprehensive Review[J]. SECURITY AND PRIVACY, 2024.

[3]. Wang Y, Su Z, Zhang N, et al. Learning in the air: Secure federated learning for UAV-assisted crowdsensing[J]. IEEE Transactions on network science and engineering, 2020, 8(2): 1055-1069.



# Implication of Generative AI on VFL





# Federated Learning: Attacks (Varun/Shishir)





# **Attack on Federated Learning**

#### **Main Categories of FL Attacks**

#### **Integrity Attacks**

These attacks aim to degrade the performance of the global model, causing it to make incorrect decisions.

#### Methods :

- 1. Disrupting Convergence (Model Poisoning)
- 2. Data Poisoning
- 3. Backdoor Injection

#### **Privacy Attacks**

These attacks attempt to infer or reconstruct private

user data, leading to privacy breaches.

#### Methods :

- 1. Inference Attack
- 2. Gradient Leakage Attack
- 3. Model Stealing Attack

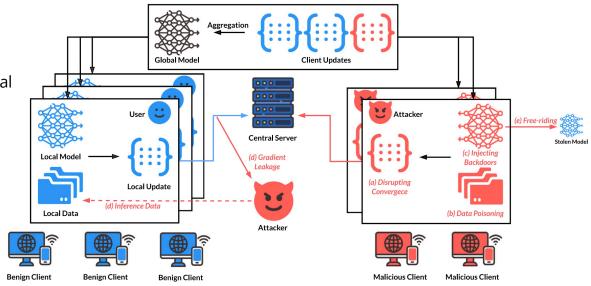


Fig. 1. An overview of common vulnerabilities in FL. Malicious attackers can: (a) manipulate model updates to prevent the global model from converging; (b) tamper data labels to induce erroneous predictions after training; (c) inject backdoors into the global model; (d) reconstruct data or inference data properties by eavesdropping model updates; (e) steal the global model while contribute nothing. <sup>[1]</sup>

[1]. Xie, Xianghua, et al. "A survey on vulnerability of federated learning: A learning algorithm perspective." Neurocomputing (2024): 127225.



# **Potential Risks of Federated Learning**

### **Model Poisoning**

**Attack Method**: Malicious drones/satellites inject tampered gradients to corrupt the global model.

#### **Examples:**

- 1. Misclassifying enemy drones as friendly.
- 2. Manipulating AI-driven traffic control to create congestion.

### **Data Poisoning**

**Attack Method**: Injecting incorrect or mislabeled data during local training.

#### Examples:

Introducing false GPS coordinates to mislead other drones' navigation systems.

### **Backdoor Attack**

**Attack Method**: Embedding hidden triggers that activate malicious behavior under specific conditions. **Examples:** 

Ignoring enemy vehicles with specific camouflage patterns.

### **Gradient Leakage Attack**

**Attack Method**: Reconstructing original training data by analyzing gradients.

#### **Examples:**

Extracting sensitive images captured by drones.

### **Inference Attack**

**Attack Method**: Determining if a specific sample was used in model training.

#### **Examples:**

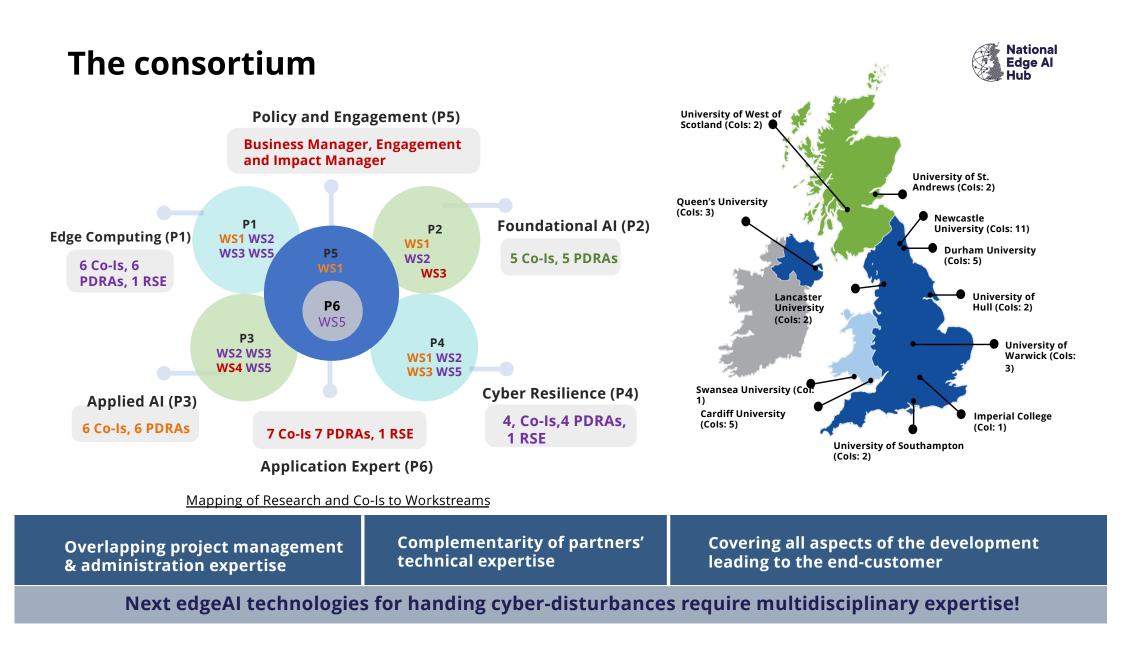
Identifying if a drone has surveyed a restricted area.

### **Model Extraction Attack**

Attack Method: Reverse-engineering the model by repeatedly querying it.

#### Examples:

Stealing an AI-based traffic control system to gain insights into urban infrastructure.





## Get in touch

### A

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