

# Exploring the Synergies between Federated Learning, Collaborative Robotics, and Autonomous Systems: Shaping the path to Industry 5.0

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## KEYWORDS

Industry 5.0, Collaborative Robotics, Autonomous Systems, Federated Learning, Human Machine Collaboration, Disaster Management

## ABSTRACT

The advent of Industry 5.0 marks a transformative era in industrial development, where advanced technologies converge to create more intelligent, efficient, and human-centric systems. This paper examines the synergistic integration of Federated Learning (FL), Collaborative Robotics (cobots), and Autonomous Systems (AS), exploring their combined potential in shaping the trajectory toward Industry 5.0. We present a comprehensive analysis of how these technologies collectively enhance the capabilities of industrial systems, with emphasis on human-machine collaboration, resilience, adaptability, and sustainability. A case study centred on a disaster response scenario is introduced to illustrate the practical benefits of this technological convergence in real-world, high-stress environments. Our findings clarify that the convergence of these technologies not only propels the industrial sector toward the visionary goals of Industry 5.0 but also opens new avenues for addressing complex challenges across various industrial and societal domains.

## 1 Introduction

In recent decades, the industrial sector has witnessed significant transformations, largely propelled by advancements in automation. This evolution culminated in Industry 4.0 Lee et al. (2014), characterised by the adoption of digital technologies, automation, and data-centric decision-making through the integration of cyber-physical systems (CPS). The dawn of the next industrial revolution—Industry 5.0—builds on these foundations while introducing a distinctly different priority: the collaboration between humans and intelligent machines, underpinned

by cognitive technologies and a commitment to human well-being.

Industry 5.0 promises unprecedented levels of adaptability and resilience within the industrial domain. It represents a pivotal shift in industrial history, characterised by the blending of human ingenuity with machine capability rather than the displacement of one by the other. Exploring the scholarly landscape of Industry 5.0 reveals three key technologies that exemplify this paradigm: federated learning (FL), collaborative robotics (cobots), and autonomous systems (AS). Each plays a crucial role in propelling industry towards more adaptive, intelligent, and sustainable practices.

Existing surveys address individual aspects of these technologies in isolation. Some focus solely on FL Li et al. (2020a), others on cobots Zafar et al. (2024), and others still on autonomous systems in industrial contexts Chi et al. (2022). To the best of the authors' knowledge, no prior survey examines the collective interplay of all three technologies within the Industry 5.0 framework. This paper addresses the following research questions:

- **RQ1:** What are the primary characteristics, enabling technologies, and applications of Industry 5.0?
- **RQ2:** In what ways do FL, collaborative robotics, and AS synergistically augment the functionalities of Industry 5.0 applications?
- **RQ3:** What are the potential advantages and present obstacles associated with implementing these synergies in the context of Industry 5.0?

The rest of the paper is structured as follows. Section 2 provides an overview of Industry 5.0 and its key application domains. Section 3 discusses federated learning. Section 4 covers collaborative robotics. Section 5 addresses autonomous systems. Section 6 explores the synergies among these technologies. Section 7 presents a disaster scenario case study, and finally a conclusion is presented.

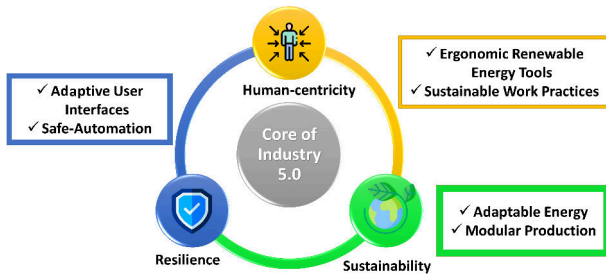


Figure 1: Industry 5.0 core principles.

## 2 Industry 5.0: A Brief Overview

The transition from Industry 4.0 to Industry 5.0 represents a significant advancement in how technology and human capabilities are integrated. While Industry 4.0 focused on automation and data exchange in manufacturing, Industry 5.0 takes a further step by emphasising the collaboration between humans and intelligent machines Xu et al. (2021). This transition involves the development of advanced technologies—including artificial intelligence, robotics, autonomous systems, and augmented reality—with the core purpose of creating inclusive, human-centric, and sustainable industrial processes that prioritise societal well-being alongside productivity.

According to the European Commission Commission et al. (2021), Industry 5.0 is defined as a movement towards a more sustainable, resilient, and human-centric industry. (See Figure 1).

### Applications of Industry 5.0

Industry 5.0 principles are being applied across a broad range of sectors. In healthcare, the shift from data-centric to human-centric design is enabling AI, IoT, and big data analytics to support continuous health monitoring, personalised medicine, and proactive disease prevention. Wearable remote monitoring expands accessibility in rural regions while reducing the carbon footprint of in-person visits Chi et al. (2023). Federated and hybrid learning allow institutions to train shared models on sensitive clinical data without centralising patient records, addressing privacy and regulatory constraints simultaneously Wazid et al. (2023).

In supply chain management, blockchain provides tamper-proof, auditable ledgers across distributed networks, cloud platforms enable real-time inventory and life-cycle data sharing, and digital twins support sustainability by reducing polluting materials in manufacturing Silva et al. (2022). ML applied to worker behavioural data further enables ergonomic monitoring to safeguard employee well-being during logistics operations Aloini et al. (2021).

Sustainable manufacturing within this framework extends beyond environmental goals to embody the Triple Bottom Line—integrating economic, social, and environmental dimensions. Collaborative robots and additive manufacturing enable more precise, flexible, and waste-reducing production, supported by capabilities such as

strategic adaptability, sustainable business model innovation, and the smartification of work environments Geissdoerfer et al. (2018).

Disaster management is among the most compelling application domains. IoT sensors provide early environmental warnings, AI algorithms analyse satellite imagery and sensor streams to predict disaster trends, and UAVs extend search-and-rescue reach into hazardous areas Moosavi et al. (2024). Cloud computing enables coordination across emergency services and government agencies. The 2018 Indonesia earthquake highlighted the limitations of Industry 4.0 approaches and the value of integrating human expertise with AI and IoT for more effective disaster mitigation Sukmono and Junaedi (2020).

## 3 Federated Learning (FL)

Federated learning is a decentralised approach to machine learning in which model training is distributed across a network of devices or servers rather than consolidated in a single location. Data remains on local devices throughout the training process; only model parameters are exchanged, which directly addresses privacy, security, and data protection concerns that arise with traditional centralised ML pipelines. The growing significance of FL in industry is evident from the upward trend in related research activity observed in recent years, reflecting increasing investment in FL as a cornerstone technology for smart, interconnected industrial systems.

FL has found application across a wide range of problem domains. Beyond mobile keyboard prediction (Gboard Hard et al. (2018)), FL enables secure cross-institutional analytics in healthcare, where sensitive patient data cannot be pooled in a centralised repository. In autonomous vehicles, FL allows fleets to share driving policy improvements without exposing proprietary route or passenger data Liu et al. (2020a). For industrial AI, frameworks such as PEFL Hao et al. (2019) and CEFL Zhou et al. (2020)—which coordinates cloud and edge devices using Lyapunov optimisation—demonstrate how FL can be adapted for commercial applications with strict data-security requirements. Blockchain-integrated FL architectures such as BlockFL Kim et al. (2019) further enhance accountability and traceability by making model update contributions auditable across federated networks.

### Types of Federated Learning

FL can be categorised based on data distribution characteristics and deployment context. Horizontal FL applies when datasets share the same feature space but differ in their samples—as with two companies offering the same service in different regions. A federated model is trained across these datasets to broaden sample coverage, with differential privacy McMahan et al. (2018a), homomorphic encryption Aono et al. (2017a), and secure aggregation Chen et al. (2018b) serving as standard privacy mechanisms. Google's Gboard exemplifies this design, updating keyboard models locally on Android devices

and transmitting only parameters to the cloud Liu et al. (2020b).

Vertical FL applies when organisations share overlapping users but hold different feature sets—a bank and an e-commerce platform, for instance, each possessing complementary data on the same individuals. Vertical FL combines these feature sets in an encrypted state without exposing raw data, as demonstrated by the SecureBoost framework Vaidya and Clifton (2002) and the vertically federated logistic regression model proposed by Hardy et al. Cheng et al. (2019).

Deployment context introduces a further distinction. Cross-Silo FL involves a small number of well-resourced institutional participants, such as hospitals or manufacturing plants, assumed to be reliably available throughout training. Cross-Device FL handles large populations of mobile or IoT devices with intermittent availability, where client selection strategies and incentive design are critical for ensuring representative and fair participation Yu et al. (2020).

### Challenges in FL

FL's primary motivation is data privacy, yet maintaining it introduces design complexity. Model aggregation compiles parameters from each node into a global model without transmitting raw training data Chen et al. (2018a), but more robust guarantees require additional mechanisms. Homomorphic encryption allows computations directly on encrypted data so that no intermediate party can reconstruct underlying information Aono et al. (2017b), while differential privacy introduces controlled statistical noise into updates such that individual records cannot be inferred from aggregate outputs McMahan et al. (2018b). Each mechanism adds computational overhead, creating tension between privacy strength and system efficiency.

Beyond privacy, three operational challenges arise particularly in cross-device settings. Edge device reliability is constrained by battery life and connectivity—mid-training dropouts bias the global model toward remaining participants, motivating approaches such as WGAN-based communication minimisation Yan et al. (2020) and hierarchical energy-efficient pacing Li et al. (2019). Data imbalance is pervasive, as local datasets across geographically diverse clients are rarely independent and identically distributed, leading to slower convergence and reduced global model accuracy van Berlo et al. (2020). Communication cost grows prohibitively as client count scales, since each round requires broadcasting the global model and collecting local updates; gradient sparsification Sun et al. (2020) and structured communication compression Li et al. (2020b) reduce this overhead without substantially degrading model quality.

## 4 Collaborative Robotics (Cobots)

The introduction of robots into industry marked a significant turning point in manufacturing and production. Early industrial robots, typified by the Unimate robot introduced

in 1961 Van de Gevel et al. (2013), operated within fixed, pre-programmed parameters confined to heavily controlled environments. They performed monotonous, hazardous, or physically demanding tasks—welding, painting, assembly—with precision and consistency, but they were inflexible and required safety cages to prevent accidental contact with human workers.

Over the following decades, advances in computing, sensor technology, and AI progressively transformed what robots could do and where they could safely operate. By the late twentieth and early twenty-first centuries, robots began to move beyond single-task operations toward more versatile, context-aware machines. This evolution proceeded through several stages: from basic *collision avoidance* systems that could detect and react to nearby humans, through *Human–Robot Interaction (HRI)* in which robots responded to social and verbal cues, to *Human–Robot Collaboration (HRC)* in which robots actively cooperated with human partners on shared tasks in close proximity Galin and Meshcheryakov (2019). The subsequent stage, *Physical Human–Robot Collaboration (pHRC)*, introduced direct physical interaction—tool sharing, joint object manipulation—requiring advanced control systems to keep human and robot actions safely coordinated Ogenyi et al. (2019).

As we enter the era of Industry 5.0, the peak of this trajectory is termed *Human–Robot Teaming (HRT)* Baskaran and Adams (2023), in which robots integrate into human work and social environments as genuine partners. Sophisticated AI and ML algorithms enable robots to predict and adapt to subtle changes in human behaviour and decision-making, making them active contributors rather than passive tools. Cobots—collaborative robots—are the practical realisation of this vision: designed for shared workspaces, equipped with sensors and safety systems sophisticated enough to operate alongside humans without cages or fences Maurice et al. (2017), as illustrated in Figure 2. Table 1 summarises representative AI/ML-based cobot deployments across personal and industrial applications.

### Key Features of Cobots

ML and AI are pivotal to the functionality of cobots in Industry 5.0. These technologies empower cobots to learn from data, adapt to new tasks, and operate autonomously in complex and dynamic environments Borboni et al. (2023). Unlike traditional programmed robots, ML-enabled cobots can develop new skills from contextual knowledge gained through experience and real-time data, allowing them to handle novel challenges as they arise. Deep learning—the most advanced form of ML, structured as multi-layer neural networks—underpins the most capable recognition and decision-support functions in modern cobots Semeraro et al. (2023).

Edge computing brings computational power to the point of data generation, enabling real-time processing and decision-making without the latency introduced by transmitting data to remote servers. For cobots, this

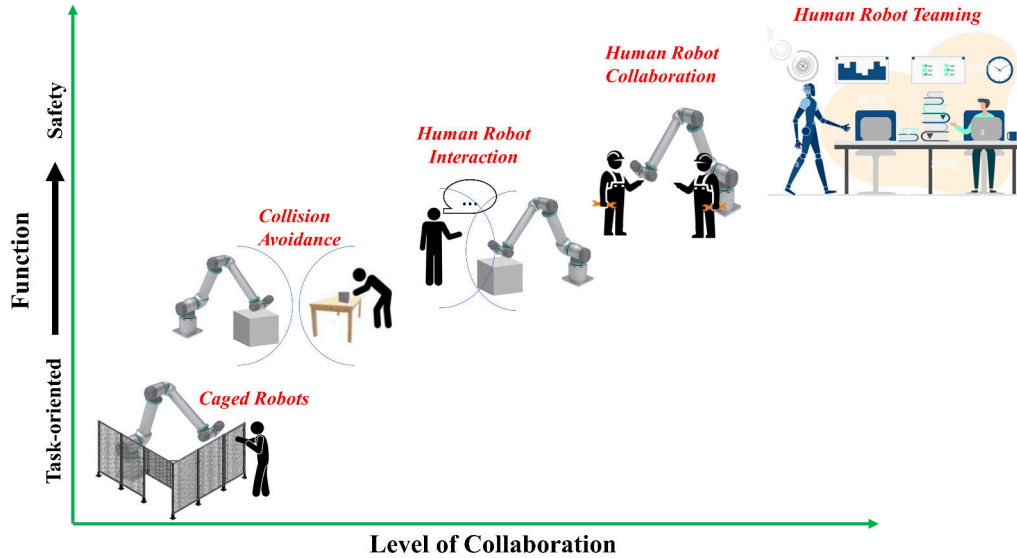


Figure 2: Evolution of the cohabitation of robots and humans.

means immediate responses to dynamic production conditions—performing inline quality inspections, detecting defects, and adjusting processes in real time Nain et al. (2022). Edge computing also enhances reliability by reducing dependence on continuous internet connectivity: cobots continue to function effectively even during network outages, maintaining operational continuity. Furthermore, running ML models locally enables cobots to learn and adapt without exposing training data to external infrastructure, adding a privacy dimension that aligns with FL principles.

Modern sensor technology has evolved from simple mechanical detectors to sophisticated multi-modal systems capable of measuring force, torque, proximity, and visual data simultaneously Javaid et al. (2021). This capability is fundamental to cobots operating in unpredictable shared environments. Vision and proximity sensors enable navigation and obstacle avoidance; force and torque sensors ensure materials are handled with appropriate pressure to prevent damage; thermal and acoustic sensors extend situational awareness into domains beyond visible light George et al. (2023). Together, these perception systems allow cobots to interact with their environment with a nuance and safety that previous generations of industrial robots simply could not achieve.

A digital twin is a virtual model of a physical system that incorporates real-time sensor data to mirror the behaviour of its real-world counterpart Soykan et al. (2025). For cobots, digital twins enable continuous performance monitoring, early detection of faults by comparing expected and observed behaviour, and maintenance scheduling before failures occur—all without interrupting production. Cloud robotics complements this by providing access to large-scale computational resources and shared knowledge bases, allowing cobots to offload intensive calculations, update ML models using collective data from

across a fleet, and benefit from the accumulated operational experience of peer systems.

As model-based learning becomes central to robotic operation in Industry 5.0, concerns around data privacy and network robustness have become critical design constraints. Proprietary process data, product specifications, and operational patterns represent commercially sensitive information that manufacturers are understandably reluctant to centralise in shared repositories. Integrating FL into collaborative robotic systems provides a principled solution: robots within a network can improve a shared global model by contributing locally computed parameter updates, without transmitting the underlying data that generated those updates. Figure 3 illustrates the resulting infrastructure—spanning user interfaces, simulation environments, digital twins, and cloud network layers—that supports FL-enabled collaborative robotics in an Industry 5.0 setting.

## Challenges

Despite their promise, cobots face a number of substantial challenges before widespread deployment can be realised. Integrating them into legacy industrial systems requires not only technical adaptation—retrofitting equipment, updating software, redesigning workflows—but also broader managerial and human-dimensions planning, since incumbent processes were designed without advanced robotics in mind. Ensuring physical safety in dynamic, unpredictable environments demands rigorous validation of sensing and response algorithms, while ensuring psychological safety requires transparent communication so that workers develop genuine trust in their robotic colleagues. Ethical questions about the autonomy and moral status of increasingly capable cobots are beginning to attract serious attention. Interoperability across multi-vendor ecosystems, cybersecurity as cobots join industrial networks, and the

| Ref                        | Year | Robot type                       | Sensing Apparatus                | Task                                          | Remarks                                                                                                                              |
|----------------------------|------|----------------------------------|----------------------------------|-----------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------|
| Buet et al. (2025)         | 2025 | UR5e                             | Vision Camera                    | Collaborative Assembly                        | Vision HRI enabling gesture-driven interaction between operator and cobot during shared assembly tasks                               |
| Shah et al. (2025)         | 2025 | Multiple (Automotive, Logistics) | Vision and Force-Lim. Sensors    | Adapt. Manufacturing and QA                   | Reviews AI/ML integration in cobots across automotive, healthcare, and logistics sectors                                             |
| Reis (2024)                | 2024 | Sawyer                           | Vision and Force Sensors         | Café Service Delivery                         | Sawyer robotic arm, employed at Henn na Café in Japan provides coffee and associated disposal tasks                                  |
| Sharma (2024)              | 2024 | Fanuc's CRX-10iA                 | Vision and Force Sensors         | Inspection work                               | A digital twin for EV battery module quality inspection using cobot                                                                  |
| Moosavi et al. (2024)      | 2023 | Snake Robot, UAVs                | Vision sensor                    | Disaster and Recovery task                    | A simulation framework involving cobots and firefighters was developed to provide aid to victims                                     |
| Lv et al. (2022)           | 2022 | Industrial Robotic Arm           | 2D/3D camera, touch sensors      | Social Interaction                            | Reinforcement learning based actions such as handshake, eye contact, smile                                                           |
| Silva et al. (2022)        | 2022 | Baxter mobile base               | 2D cameras with 1280x720, 30 FPS | Homographic pixel mapping                     | Developed a method for direct robot control using video streams and deep learning for real-time mapping and interactive control      |
| Weiss et al. (2021)        | 2021 | UR10                             | Sensors                          | Assembling combustion engine, polishing molds | Using EEG and LSTM-RNN to quickly recognise upper-limb movement intents for safer human-robot collaboration                          |
| Aliev and Antonelli (2021) | 2021 | UR3                              | Sensors, Real-time data exchange | Predict outages and safe stops                | Online monitoring system using ML and sensors to predict cobot breakdowns and safe stops by analysing physical and event parameters. |

Table 1: Summary of AI / ML based cobots for enhancing human tasks in personal and industrial applications

upfront capital cost—particularly for small and medium enterprises—all present further barriers that will require coordinated industry and policy responses.

## 5 Autonomous Systems (AS)

In the face of rapidly evolving market demands, manufacturers are under pressure to ensure their production lines are not merely efficient but also adaptive, intelligent, and flexible. Autonomous systems—machines capable of performing complex tasks independently of direct human intervention—are central to meeting this challenge in Industry 5.0. Unlike conventional automation, which executes fixed, pre-programmed sequences, autonomous systems leverage AI to learn from data, respond to unforeseen conditions, and continuously improve their own performance Nahavandi (2019).

The primary motivations for deploying autonomous systems in industry are well-established: managing the complexity of large-scale systems of systems through autonomous components Zhou et al. (2019); enhancing resilience under inherent uncertainties; reducing the cognitive and operational burden on human controllers; and enabling operations in conditions where remote control is

impractical or unsafe.

### Role of AI and Deep Learning

Artificial intelligence is the enabling force behind autonomous systems in Industry 5.0. Deep learning, in particular, automates the extraction of meaningful features from raw sensor and production data, allowing autonomous systems to perform tasks—classification, regression, anomaly detection—that previously required direct human intervention. Transfer learning further allows systems to adapt knowledge gained in one context to new, related tasks, which is especially valuable in the unpredictable operational conditions characteristic of Industry 5.0 environments. Autonomous systems driven by these methods can engage in real-time decision-making, predictive maintenance, and dynamic process optimisation—capabilities that are central to the vision of self-regulating industrial production.

### Potential Impact

The integration of autonomous systems into Industry 5.0 holds transformative potential across several dimensions.

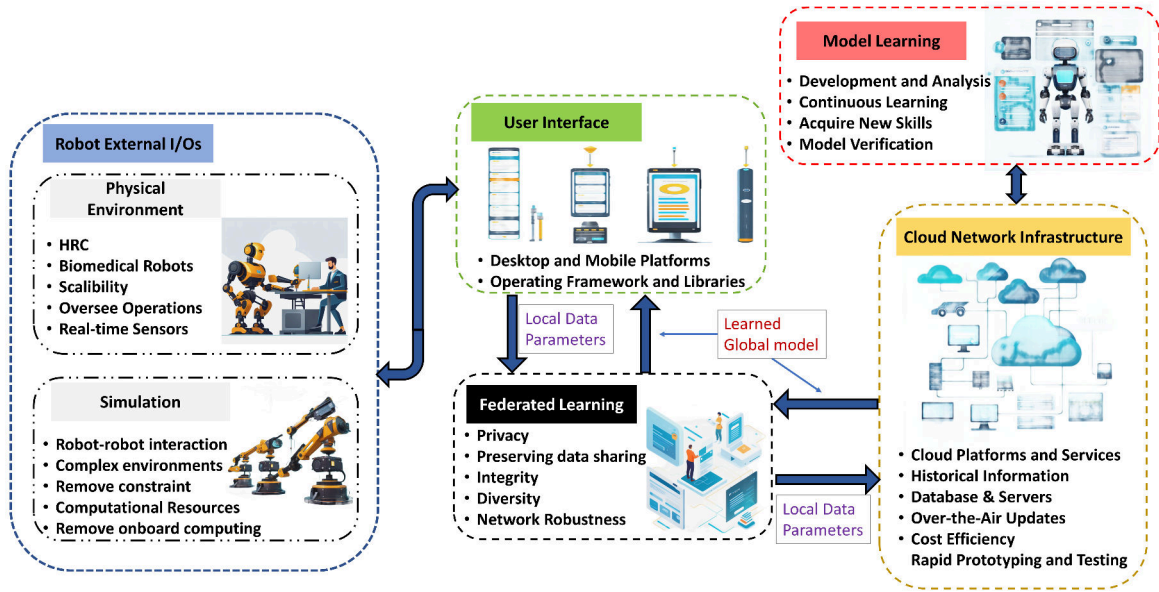


Figure 3: Collaborative Robotics Systems Infrastructure with Federated Learning Mechanism: A roadmap.

Operational efficiency improves through 24/7 operation, consistent quality control, and proactive identification of equipment issues before failures occur. Mass customisation becomes feasible when autonomous systems can dynamically reconfigure production lines in real time to accommodate individual customer requirements without sacrificing the throughput typical of mass production. Workplace safety improves as autonomous systems take over hazardous tasks involving heavy lifting, toxic materials, or extreme temperatures. Sustainability efforts are supported through optimised energy management and reduced material waste Maddikunta et al. (2022).

## Challenges

The integration of autonomous systems is not without difficulty. Interoperability across heterogeneous device ecosystems lacking shared protocols remains a persistent technical barrier. The sheer volume of data generated by autonomous systems creates demands on storage, processing, and real-time analytics infrastructure. Cybersecurity risks are amplified as more systems connect to industrial networks—autonomous decision-making creates new attack surfaces, and failures can have immediate safety consequences. Ethical questions around autonomous decision-making—particularly regarding accountability when things go wrong—remain unresolved. A skills gap is widening as the workforce required to develop, maintain, and collaborate with autonomous systems does not yet exist at the scale needed. Regulatory frameworks are evolving, but the pace of technological change consistently outstrips the pace of standardisation Jahan et al. (2019).

## 6 Synergies and Interactions

The convergence of FL, cobots, and AS within Industry 5.0 produces capabilities that none of these technologies achieves independently. Three principal synergies are identified below.

**Collaborative Learning and Efficient Data Processing.** Federated learning allows autonomous systems and robots to learn from localised data while contributing to a shared global model—mirroring the collaborative way humans accumulate knowledge. Deep learning enhances this process, enabling machines to draw accurate inferences from distributed industrial data and analyse high-dimensional sensor streams rapidly. By offloading intensive computation to cloud infrastructure while retaining edge-level responsiveness, the integrated system balances the scale of cloud processing against the latency demands of real-time industrial control—yielding a network that improves continuously without any single node requiring access to the full data ecosystem.

**Augmented Autonomy and Privacy-Preserving Learning.** FL’s fundamental design—training on local data and sharing only model updates—simultaneously delivers two critical properties. First, it enables autonomous systems to adapt to diverse local conditions while maintaining coherence with a global perspective accumulated across the fleet, making individual systems far more adaptive than any centralised alternative. Second, it ensures that sensitive manufacturing data, including proprietary processes, product designs, and customer information, never leaves the organisation’s premises—directly addressing one of the most significant barriers to deploying shared ML systems in competitive industrial environments where data privacy is both a legal obligation and a commercial imperative.

**Human-Centric AI Integration.** The essence of In-

dustry 5.0 lies in augmenting rather than replacing human capability. FL, cobots, and AS embody this principle: machines learn from human expertise, share that learning across the network, and free workers from routine and hazardous tasks to focus on creative, strategic, and interpersonal roles. The result is a genuine symbiosis in which humans and machines each contribute what they do best.

These synergies introduce cross-cutting challenges. Data privacy and security must be maintained across the full integrated technology stack. Interoperability across diverse devices, vendors, and protocols is a prerequisite for seamless collaboration. FL model scalability grows increasingly complex as connected devices multiply. Real-time processing demands must be balanced against cloud communication latency. And regulatory compliance across robotics safety, data protection, and AI ethics requires ongoing attention as standards continue to evolve.

## 7 Use Case: Disaster Environment

**Scenario Setup.** Emergency management is one of the most compelling application domains for the technologies discussed in this paper. This section presents a conceptual framework combining cobots, autonomous systems, deep learning, and federated learning to address a disaster scenario within the Industry 5.0 paradigm. To the best of the authors' knowledge, no integrated model of this nature has been proposed in the prior literature.

The scenario involves a metropolitan area struck by multiple simultaneous natural disasters: building collapses, extensive debris fields, structural fires, and flooding have placed an unknown number of civilians in immediate danger. While current practice relies largely on remotely-operated vehicles guided by a human operator, the framework proposed here deploys a team of autonomously capable robots that eliminate the need for continuous remote manipulation while preserving meaningful human oversight. The team consists of: a snake robot with thermal sensors for confined-space navigation and fire detection Moosavi et al. (2024); a LiDAR-based quadruped for traversal across debris fields and unstable terrain Sanfilippo and Rañó (2023); underwater marine vehicles for flooded areas; and UAVs providing high-altitude situational awareness. All assets communicate with one another and with human operators through a federated learning infrastructure on cloud architecture, as illustrated in Figure 4.

**Integration and Coordination.** What distinguishes this framework from conventional disaster robotics is the degree of inter-robot communication and collective decision-making enabled by the FL infrastructure. Each robot continuously assesses conditions in its assigned area and relays relevant observations to the team. Through federated learning and cloud-based analytics, priority tasks are allocated based on urgency, coverage gaps are minimised, and resource assignment updates continuously as conditions change. Human operators monitor and guide

the robots as needed via bidirectional communication, preserving critical oversight while allowing autonomous systems to operate independently where human access is dangerous or impossible.

**AI for Situation Awareness.** Deep learning models provide the cognitive foundation for autonomous operation. CNNs process real-time visual and thermal data to identify survivors, classify structural hazards, and navigate debris fields. RNNs capture the temporal dynamics of a rapidly evolving scene, enabling robots to anticipate emerging conditions rather than simply reacting to the present state. NLP capabilities extend situational awareness into direct survivor interaction: a robot can initiate dialogue, interpret injury severity from verbal responses, and relay priority information to human responders—particularly valuable when language barriers or trauma complicate communication. Deep learning models update continuously from new observations, maintaining decision quality under high uncertainty.

**Federated Learning for Secure Collaboration.** FL's decentralised model is especially valuable in disaster environments where communication infrastructure may be damaged or severely bandwidth-constrained. Each robot maintains operational autonomy from its most recent local model, continuing to navigate, assess, and act even when disconnected from the central server. Only model updates—not raw sensor data or victim imagery—are transmitted when connectivity is available, reducing network load and protecting sensitive data. When connectivity is restored, locally computed updates synchronise across the fleet, ensuring insights gained in one part of the disaster zone propagate to all assets. This architecture delivers operational resilience, data efficiency under bandwidth constraints, and principled privacy preservation—demonstrating FL's value well beyond conventional industrial settings.

## Conclusion

This paper has examined the synergistic potential of federated learning, collaborative robotics, and autonomous systems within the Industry 5.0 paradigm, demonstrating how their convergence produces capabilities that none achieves independently. The disaster management case study grounds this convergence in a high-stress real-world context, where autonomous robotic teams coordinated through FL and guided by deep learning extend the reach of human first responders while preserving meaningful human oversight. Critical challenges—data privacy and security, interoperability standardisation, FL scalability, real-time processing constraints, and an evolving regulatory landscape—require sustained and coordinated responses from industry, regulatory bodies, and academia. The convergence examined here is not a finished architecture but a set of demonstrated synergies that establish the foundation for industrial and societal advancement grounded in human well-being, environmental responsibility, and equitable access.

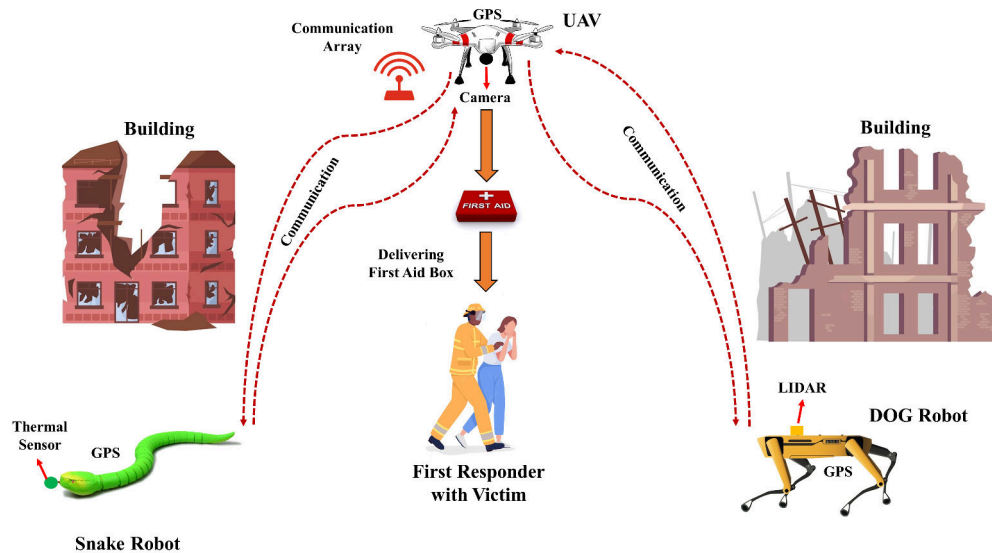


Figure 4: First responders attending to a disaster scenario utilising AI-driven, self-aware robots for emergency management. The scenario integrates decentralised federated learning, collaborative robotics, and autonomous systems, exemplifying Industry 5.0 principles in a high-stakes real-world context.

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