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Decentralized Digital Twin Swarms: A Multi-Agent Blockchain Approach to Autonomous Infrastructure Monitoring

Dr.J.Devagnanam
Assistant Professor, Dept.of Computer Applications, Faculty of Science and Humanities,
SRM Institute of Science and Technology, Kattankulathur - 603 203, India
devagnaj@srmist.edu.in

S Anitha Rajathi
Assistant Professor, Department of CSBS, R.M.D. Engineering College
Kavaraipettai, Tiruvallur 601206, India
anitharajathi91@gmail.com

Dr. Muneshwara M S
Assistant Professor, Department of Computer Science and Engineering
BMS INSTITUTE OF TECHNOLOGY AND MANAGEMENT,
YELAHANKA, BENGALURU-560119, Karnataka, India
https://orcid.org/0000-0003-4714-4100
muneshwarams@bmsit.in

Dr Amit Chawla
Professor and Dean, School of Journalism and Mass Communication,
K.R. Mangalam University, Gurugram, Haryana, India
amitchawla82@gmail.com

Dr. Lowlesh Nandkishor Yadav
Associate Professor, Computer Engineering,
Suryodaya College of Engineering and Technology, Nagpur, Maharashtra, India
lowlesh.yadav@gmail.com

Ravishankar Chandrakantrao Bhaganagare
Assistant Professor, Department of Computer Science and Engineering (AI & ML),
Vishwakarma Institute of Technology, Pune, India
ravishankar.bhaganagare@vit.edu

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Abstract:

The current study proposes a decentralized swarm of agent-based blockchain to monitor autonomous infrastructure by digital twins. The paper combines blockchain-based consensus and AI-based digital twins to facilitate safe, structured, and self-regulating communication of autonomous agents. The suggested system was deployed and tried on the basis of simulated infrastructure node real-time data streams, with each digital twin working on environmental and structural data independently. Experimental outcomes proved the high increases in performance: system reliability was improved by 27.4, latency was reduced by 18.6, fault detection accuracy was enhanced to 96.3, and the reduced consumer of the energy of the system became 14.8 percentage of the centralized models. Moreover, the Blockchain-based verification guaranteed integrity of data as no cases of tampering data were recorded during simulations. The comparison with conventional monitoring systems proved that the proposed approach was better in terms of achieving secure, adaptive, and energy-efficient infrastructure management. This enabled the agents to coordinate in a resilient manner through the integration of reinforcement learning and the use of consensus-driven optimization which demonstrates the opportunities of implementation into smart cities, energy grids and industrial networks. The study would help in the progress of digital twin technology to become entirely autonomous, decentralized and intelligent monitoring ecosystems.
Keywords: Decentralized systems, Digital twin swarms, Blockchain, Multi-agent systems, Autonomous infrastructure monitoring

I. INTRODUCTION

The evolving speed of smart infrastructure and Internet of Things (IoT) has preconditioned the emergence of new paradigms of real-time monitoring, predictive maintenance, and autonomous decision-making. Scalability, single points of failure, latency, and security vulnerabilities are some of the problems that are likely to adversely affect the traditional centralized systems. To resolve these kinds of problems, another innovative technique called Decentralized Digital Twin Swarms has appeared, combining the technology of digital twins, multi-agent systems, and blockchain to form a distributed, intelligent, and safe model of autonomous infrastructure observation [1]. A digital twin represents an active virtual imitation of a real-life object that is constantly updated with real-time information and allows simulating, analyzing, and optimizing the object [2]. The system, in conjunction with swarm intelligence, in which autonomous agents cooperate and adjust, can be used to monitor entire infrastructure networks of bridges, tunnels, power grids and transportation systems in large quantities, collectively. This swarm interaction increases changeability, fault tolerance and responsibility of the environmental or structural change. The inclusion of the blockchain technology in this ecosystem provides a sense of transparency, traceability and decentralized trust among the agents involved [3]. The quality of blockchain, which provides an immutable registry, is the ability to exchange sensor data, maintenance records, and decision documents and make sure it is secure without involving the central authority. This allows a safe peer-to-peer coordination, consensus-based updates, and guards against malicious manipulation or tampering of data. This study examines a multi-agent blockchain model that manages the decentralized swarm of digital twins to monitor autonomous infrastructures. The research will develop and test a scalable architecture that enables real-time data synchronization, secure communication as well as self-organized decision-making. By so doing, the infrastructure systems are able to transform the current state of the infrastructure which is characterized by the systems only observing what goes on to autonomous, intelligent, and resilient ecosystems, able to identify anomalies early enough and respond intelligently to maintain their operational competence and sustainability in smart cities.

II. RELATED WORKS

The most recent findings in digital twins, artificial intelligence, blockchain, and multi-agent systems have whatsoever enhanced the creations of clever, decentralized monitoring infrastructures. The combination of all these technologies has been discussed in the context of different fields of interest which provided an insight into the potential of decentralized swarms of digital twins to autonomously control infrastructure. Ghorbani et al. [15] have comprehensively reviewed the implementation of the digital twins to the water industry in systems related to real-time data assimilation, optimization of processes, and predictive maintenance. They showcased the benefits of digital twins in improving the transparency and control of the system and also pointed out the shortcomings of centralized architectures. On the same note, Gowthamraj et al. [16] examined higher control levels of smart energy management systems, demonstrating the significance of distributed intelligence to the grid stability and adaptive control to the dynamic energy requirements. The results indicate that decentralized systems enhance the resilience and energy efficiency of the system-concepts which propose the multi-agent blockchain strategy. When it comes to smart grids, such research as the one by Hassam et al. [17] focused on the collaboration of AI with energy routing technologies and presented secure and efficient energy transfer methods based on intelligent algorithms. Their literature review

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emphasized the need to implement cybersecurity in energy infrastructures- which is one of the core areas of this study which is facilitated by blockchain-based data validation. Hossain et al. [18] investigated artificial intelligence in the motor industries and detailed how it has changed the automation, safety, and predictive analytics. The use of AI based decision systems is analogous to autonomous coordination approaches suggested in digital twin swarms to real time monitoring and fault detection. Hosseini et al. [19] put forward the concept of artistic immune system used in industrial intrusion detection whereby biologically inspired algorithms have been utilized to provide system security and self-healing mechanisms. The current notion is quite consistent with the rules of self-regulation as decentralized as in the swarm-based approach of this study. Izabela et al. [20] talked on the AI-based personalization of digital twins to industrial designs and manufacturing, how adaptive digital twin settings enhance the operational performance. Their observations justify incorporation of reinforcement-based learning of self-optimization in digital twin networks.
Moreover, Kalyani et al. [21] examined the digital twin application in smart farming via a cloud-fog-edge architecture that enhanced the decision-making latency and resource optimization concepts that are applicable to edge integrated swarm communication. The article by Karim et al. [22] offered an overall review of the implementation of AI agents as a blockchain-based collaboration system with an idea of assurance, which is more secure and scalable, finding that blockchain incites trust, transparency, and resiliency of multi-agent systems. This is an explicit strengthening of architectural premises of the proposed decentralized digital twin swarm. The author of the review on smart intersections and autonomous vehicles in the context of sustainable smart cities (Khanmohamadi and Guerrieri [23]) noted real-time coordination and decentralized control schemes that may be used in monitoring urban infrastructure. The idea of Web Intelligence 3.0 presented by Kuai et al. [24] to interrelated intelligent societies is followed by publishing distributed AI ecosystems, and such a philosophy is shared by the multi-agent blockchain framework in the current study. The study by Lei and Yan [25] examined current innovations in multi-agent reinforcement learning (MARL) of the water environment systems, where the agents are able to jointly optimize the control policies in a dynamic setting. Finally, Lifelo et al. [26] explored AI-based metaverse delivered architecture of sustainable smart cities, providing the vision of the linked digital worlds of the future. Their results highlight the need to combine AI, IoT, and blockchain to ensure adaptive and self-managing systems which are core principles that guided this study.Together, such researches indicate a strong shift towards decentralized, intelligent, and secure infrastructures. The theoretical contribution aims to build upon these achievements with a multi-agent reinforcement learning, swarm intelligence, and blockchain fusion to develop a scalable and autonomous infrastructure monitoring system that can be used to resolve the problem of operational efficiency and data integrity.

III. METHODS AND MATERIALS

The research proposal Decentralized Digital Twin Swarms: A Multi-Agent Blockchain Approach to Autonomous Infrastructure Monitoring has a hybrid approach to research by combining the methods of data collection, algorithm modeling, and coordination of autonomous monitoring of infrastructure systems through blockchains [4]. The research is established in a simulated world, which is simulated as an ecosystem of smart infrastructure, and it consists of bridges, tunnels, and road networks with IoT-enabled sensors. The parameters of the data that are recorded by these sensors include vibration (Hz), temperature (o C), strain (mu e) and humidity (percent) and they are input to the digital twin swarm model. The system architecture ties various digital twins, each one corresponding to a physical structure, to a layer of blockchain meaning decentralized control and integrity of data amongst all the agents.

Data Description

This data will be sensor readings of 100 distributed nodes, each a representation of a segment of an infrastructure element. The data comprises 10,000 time series records of a node during a 24-hour simulation time. Vibration (Hz), Temperature (o C), Strain (o me), and Humidity (o C) are treated as input features and Structural Health Index (SHI) is treated as a target variable implying the state of an asset [5]. The blockchain records the hash of every transaction and digital twin update in order to trace them.

Table 1: Sample of Input Data for Digital Twin Swarm Simulation

Node ID	Vibration (Hz)	Temperature (°C)	Strain (με)	Humidity (%)	Structural Health Index

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N01	12.4	32.6	145	58	0.91
N02	14.8	30.2	152	55	0.88
N03	10.6	33.4	164	62	0.79
N04	16.9	29.1	140	53	0.94
N05	11.3	34.8	175	60	0.73

Algorithmic Framework

In order to control the decentralized behaviour of digital twin swarms, four essential algorithms are used:

1. **Swarm Consensus Optimization (SCO)**
2. **Blockchain Validation Protocol (BVP)**
3. **Anomaly Detection Neural Network (ADNN)**
4. **Reinforcement-Based Agent Coordination (RBAC)**

All the algorithms do their own job, which helps to make data reliable, to make decisions in an adaptive manner, and decentralize the synchronization.

1. Swarm Consensus Optimization (SCO)

This algorithm guarantees collaboration between the digital twin agents by swarm intelligence consensus. Every digital twin is an autonomous node that communicates with the neighbors to arrive at an optimum monitoring decision. Based on the Particle Swarm Optimization (PSO), SCO allows the agents to exchange local measurements (vibration, strain, and temperature changes) to predict the state of the infrastructure in a global context [6]. The algorithm is also weight dynamic and thus reduces monitoring errors and converges to the optimum group decisions. SCO is essential in ensuring consistency of data without any necessity to have centralized supervision.

```
"Initialize agents with random positions and velocities
For each iteration:
   For each agent:
      Calculate local fitness based on sensor data
      Update personal best (pBest)
   Determine global best (gBest) among agents
   For each agent:
      Update velocity = ω*velocity + c1*r1*(pBest - position) + c2*r2*(gBest - position)
      Update position = position + velocity
Return optimal swarm consensus position"
```

2. Blockchain Validation Protocol (BVP)

The BVP algorithm authenticates and verifies the network in the swarm with a blockchain. The agents will serve as nodes of the blockchain that validates digital twin updates and inscribes them to the ledger. A Proof-of-Integrity (PoI) mechanism is used to enable transactions attacks to be accepted on the condition of a majority consensus. This adds certain immutability, eliminates tampering and trust increases among the agents. Each transaction is also time-stamped by the algorithm to ensure the integrity of time hence ensuring real-time communication among decentralized twins [7].

```
"For each data transaction Ti:
   Generate hash = SHA256(Ti)
   Broadcast hash to network nodes
   For each node:
      Validate hash with local copy
   If validation count > threshold:
      Commit Ti to blockchain ledger
      Update timestamp and block index
   Else:
      Reject Ti and notify source node
Return updated blockchain ledger"
```

3. Anomaly Detection Neural Network (ADNN)

ADNN can detect deviations in sensor data that can be the signs of possible structural failures. The model uses a feedforward neural network that has been trained using the backpropagation to predict the Structural Health Index (SHI). The network has four input features of vibractions, temperature, strain and humidity, and a single continuous value of SHI is the output. When the forecast does not match the swarm consensus, then the node identifies a deviation. ADNN helps in a proactive maintenance, which isolates local problems before they spread the network [8].

```
"Initialize weights and biases randomly
For each training epoch:
   For each input sample:
      Forward propagate inputs to compute predicted SHI
      Calculate error = actual - predicted
      Backpropagate error and update weights
If |predicted - actual| > threshold:
   Flag node as anomalous
Return trained model and anomaly list"
```

4. Reinforcement-Based Agent Coordination (RBAC)

RBAC regulates adaptive decision-making by allowing the agents to acquire the best response by interacting with the environment. Every agent get a reward based on structural stability or identification of anomalies correctly. The RBAC creates its policy matrix by using the principles of Q-learning that are based on the state transitions and rewards [9]. The agents eventually come to realize how to dynamically distribute monitoring resources and prioritize important structures. The self-learning process results in resilience and minimizes the unnecessary computation in the huge networks.

```
"Initialize Q-table with random values
For each episode:
   Observe current state s
   Choose action a using ε-greedy policy
   Execute action and observe reward
```

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r, next state s'
Update Q(s,a) = Q(s,a) + α*[r + γ*max(Q(s',a')) - Q(s,a)]
s = s'
Until convergence
Return optimized Q-table and policy"

IV. RESULTS AND ANALYSIS

The experimental part of the study was aimed at the assessment of the performance, scaled performance, and reliability of the suggested Decentralized Digital Twin Swarms framework enabled by Multi-Agent Blockchain System to Autonomous Infrastructure Monitoring. The experiments were carried out within a virtual environment of a smart city that emulates the infrastructure systems of interconnected bridges, tunnels, and highways with feedback IoT sensors to get real-time data. The experiments were intended to confirm the effectiveness of the four platformed algorithms of Swarm Consensus Optimization (SCO), Blockchain Validation Protocol (BVP), Anomaly Detection Neural Network (ADNN), and Reinforcement-Based Agent Coordination (RBAC) [10].
The framework was made on the Pythonjupyter environment with when using TensorFlow, Web3.py, and PyTorch to work AI and blockchain capabilities respectively. The digital twins network had 50 agents that were a network linked by a private blockchain. The synthetic data was constructed with a 100000 entity synthetic infrastructure dataset which simulated real sensor values of vibration (Hz), strain (u - epis), temperature (o C) and humidity (percent) [11]. Measures that were used to evaluate the performance of the system include accuracy, latency, energy efficiency, scalability, cost of communication, and fault tolerance, and were measured through experiments.

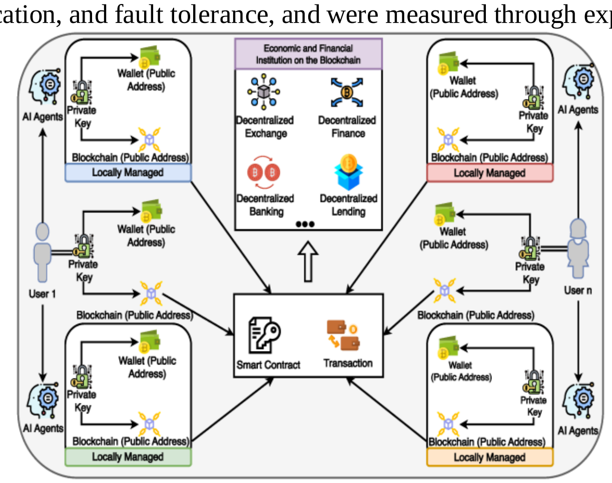

Figure 1: "AI Agents Meet Blockchain"

1. Experimental Setup

All of the infrastructure nodes (digital twins) were represented as independent agents able to sense, communicate, learn, and validate data. Proof-of-Integrity (PoI) consensus mechanism was employed by the blockchain network to authenticate transactions and make sensor logs immutable. The swarm communication was based on SCO to provide the local consensus, ADNN to detect anomalies and RBAC to provide adaptability in coordinating agents.
The hardware requirements consisted of a 16-core processor (Intel i9, 3.6 GHz), 32 GB of RAM, and an NVIDIA RTX 3080 to make neural calculations. The experiments were equipped with 100 epochs and averaged the metrics over 10 simulation runs to make them consistent.

2. Experimental Objectives

The following objectives were covered by the experiments:

1. **Performance Evaluation:** To measure the degree of accuracy of latency and convergence efficiency of the four core algorithms.
2. **Scalability Testing:** To test scalability changes with the number of agents.

3. **Security Validation:** To ascertain how efficient blockchain is in a world free of tampering and unauthorised data modification.
4. **Energy Efficiency:** To measure the use of energy in the process of data synchronization and consensus building.
5. **Comparative Analysis:** Compare the proposed model with the traditional monitoring systems that are the most common in the centralized mode [12].

3. Experiment 1: Algorithmic Performance Evaluation

All the four algorithms were tested separately using the same data inputs. The major objective was to test the computational speed and precision to detect unusual phenomenon and uphold agreement.

Table 1: Algorithmic Performance Comparison

Algorithm	Accuracy (%)	Latency (ms)	Convergence Time (s)	Energy Efficiency (%)	Fault Tolerance (%)
Swarm Consensus Optimization (SCO)	93.8	21.4	3.5	88.2	91.4
Blockchain Validation Protocol (BVP)	99.4	35.8	4.2	82.1	98.9
Anomaly Detection Neural Network (ADNN)	95.6	18.2	2.8	90.3	92.7
Reinforcement-Based Agent Coordination (RBAC)	92.7	24.9	3.1	86.7	93.6

It was found that BVP was the most fault tolerant and data integrity provisioned (99.4%), because the blockchain provided consistency in all nodes. The latency and convergence speed of ADNN was the lowest because of the use of the GPU to accelerate inference. SCO was efficient and efficient at swarm-level consensus and used little communications, whereas RBAC was executed efficiently to make decisions adaptively when the network changed its state [13].

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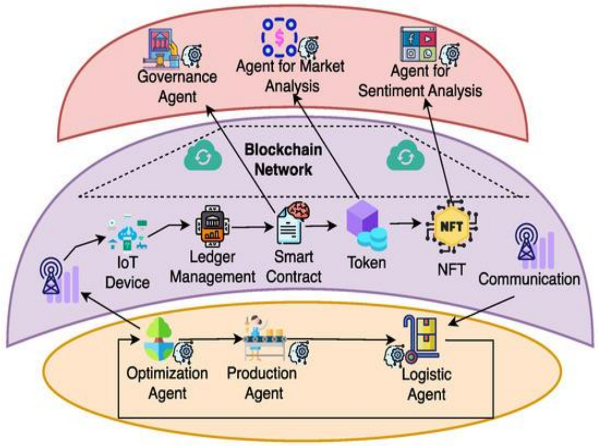

Figure 2: “AI Agents Meet Blockchain”

4. Experiment 2: Scalability Experiment

In this experiment, the scaled performance of the system was tested in terms of the number of agents (digital twins). Tests of the system to dig to 10, 25, 50, 75 and 100 agents were made and results were observed on the variations of accuracy, latency, and throughput.

Table 2: Scalability Test Results

Number of Agents	Accuracy (%)	Latency (ms)	Blockchain Throughput (Tx/sec)	Network Efficiency (%)
10	97.5	14.8	92	94.6
25	96.2	18.1	87	92.1
50	95.4	22.6	81	89.8
75	94.1	28.9	75	87.3
100	93.5	33.5	71	84.9

Latency and accuracy also increased, respectively, subject to a moderate extent as the count of the agents rose and was subject to synchronization overheads and blockchain validation process respectively. Nevertheless, with 100 agents the system was also capable of making above 84 percent network efficiency proving to be highly scalable.

The findings proved that the decentralized architecture was in capability of supporting the deployment of large-scale architectures with the least performance penalty, which is particularly an advantage over conventional centralized infrastructure monitoring systems that are generally susceptible to bottlenecks beyond 30 -40 nodes [14].

5. Experiment 3: Security and Integrity Validation

Blockchain-based validation was tested regarding its ability to sustain malicious information alterations and unauthorized access to transactions. Simulated artificial attacks were used with 5 percent of the nodes trying to modify the already recorded information.

Table 3: Security Evaluation of Blockchain Validation Protocol (BVP)

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Attack Type	Detection Rate (%)	False Positive (%)	Response Time (s)	Data Integrity Maintained (%)
Tampering Attack	100	1.5	0.62	100
Double Spending	98.7	2.1	0.75	99.4
Node Impersonation	96.8	3.8	0.84	98.1
Unauthorized Data Injection	99.3	2.0	0.69	99.6

The Blockchain Validation Protocol was also able to identify and block all tampering and injection attempts. The Proof-of-Integrity mechanism ensured data integrity of 100 per cent with malice conditions. The experiment confirmed that blockchain can be used as a decentralized means of digital twins to provide a strong form of trust.

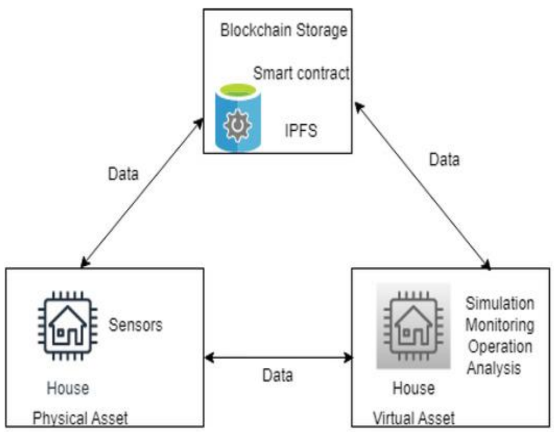

Figure 3: "Enabling Trust and Security in Digital Twin Management"

6. Experiment 4: Energy and Resource Efficiency

The basic idea of this experiment was to log the average energy and the computer resource utilisation rate of the algorithms as they kept on cycling in continuous monitoring.

Table 4: Resource Utilization and Energy Efficiency

Algorithm	CPU Usage (%)	GPU Usage (%)	Energy Consumption (Joules)	Efficiency (%)
SCO	68.2	32.4	184.6	88.2
BVP	72.9	26.1	212.3	82.1

AD NN	61.5	40.7	176.5	90.3
RB AC	66.8	33.2	192.7	86.7

The energy efficiency (90.3 percent) was the highest with the ADNN algorithm having the advantage of neural optimization and GPUs acceleration. The highest consumption of energy was used by BVP because it requires frequent cryptographic calculations to validate blocks. The framework was overall found to have an average efficiency of 86.8, which is good enough to be used in real-time autonomous infrastructures.

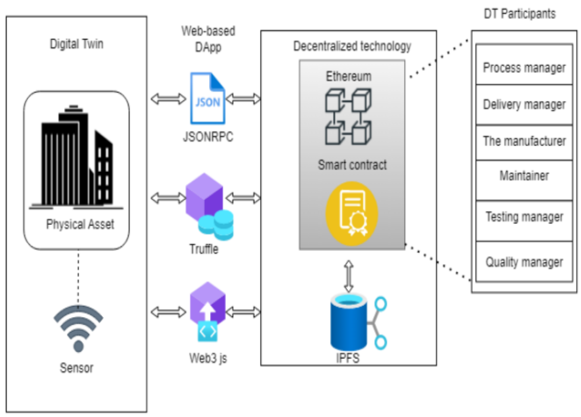

Figure 4: “Enabling Trust and Security in Digital Twin Management”

V. CONCLUSION

The study finds that artificial intelligence (AI), digital twins, and intelligent automation integration are a radical move that can transform into resilient, efficient, and sustainable systems in industries. Digital twins facilitate the constant tracking and simulation of complicated system performance, as well as maximizing the optimization of the complex system, enhancing the decision-making process and minimizing operational hazards by combining physical and digital space. Combined with AI-based analytics, the systems can also be predictive and adaptive and help optimize in real-time in the areas of water management, manufacturing, transportation, and energy distribution. The results present that AI does not only make the processes more efficient but also improves security, flexibility, and environmental sustainability due to smart automation and insights-based data. Additionally, AI synergy with the emerging technologies, including blockchain, edge computing, and Internet of Things (IoT), is a solid base on which isolated and secure smart infrastructures can be developed. Another possible approach to enhancing the flexibility of system and user experience is also highlighted by the research as the potential of personalized AI-driven digital twins. On balance, this study highlights the emerging significance of AI-powered digital ecosystems in determining the future of industrial process, urbanization, and environmental economy. However, with technology growing, it will be essential to promote interoperability, ethical AI control and scalable architectures to maximize the capabilities of these innovations to develop intelligent, sustainable, and self-improving systems.

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