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METAVERSAL INTELLIGENCE: UNIFYING HUMAN-AI INTERACTIONS IN HUMAN-IN-THE-LOOP AIB METAVERSE

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Intelligence Métaversale : Unifier Les Interactions Humain-IA Dans Le Métavers AIB Avec L'humain Dans La Boucle

Résumé

L'essor des technologies émergentes telles que la 6G, le Web 3 et la blockchain transforme profondément l'architecture des systèmes intelligents et la gestion des interactions dans des environnements numériques décentralisés. Le Métavers est une plateforme immersive en pleine évolution qui vise à intégrer les interactions humaines et artificielles dans un espace virtuel intelligent et autonome. Toutefois, l'émergence de cet écosystème numérique soulève plusieurs défis majeurs, notamment en matière d'adaptabilité, d'évolutivité, de gestion des ressources, de prise de décision et d'exécution des transactions intelligentes de manière sécurisée et efficace. L'évolution du Métavers nécessite des solutions innovantes pour assurer une collaboration efficace entre les agents humains et artificiels, optimiser les performances des contrats intelligents et améliorer l'intelligence collective dans ces environnements dynamiques.

Dans ce contexte, cette thèse propose une nouvelle architecture appelée Human-AI Blockchain (HAIB) Métavers, conçue pour améliorer la collaboration entre les utilisateurs humains et les agents IA dans un environnement virtuel décentralisé. L'architecture HAIB s'appuie sur le paradigme Human-in-the-Loop, une approche qui intègre activement l'intelligence humaine dans le processus de prise de décision des systèmes IA. Plutôt que de se limiter à des décisions purement algorithmiques, HAIB permet une interaction continue entre humains et agents autonomes, favorisant ainsi une meilleure adaptabilité et une prise de décision plus pertinente dans un cadre évolutif comme le Métavers.

Une des principales contributions de cette thèse réside dans l'introduction des Contrat Intelligent (InSC), un cadre novateur de contrats intelligents combinant apprentissage par renforcement (RL) et stigmergie étendue. Contrairement aux contrats intelligents classiques qui exécutent des instructions statiques de manière déterministe, les InSC permettent une exécution dynamique et adaptative des contrats grâce à une capacité d'apprentissage autonome. En s'appuyant sur l'apprentissage par renforcement, ces contrats améliorent leur prise de décision au fil des interactions et ajustent leurs conditions en fonction des évolutions de l'environnement. De plus, l'intégration du mécanisme de stigmergie étendue permet aux agents IA de collaborer

indirectement en laissant des traces numériques dans l'environnement, facilitant ainsi une coordination sans communication directe, inspirée des systèmes auto-organisés observés dans la nature.

L'architecture HAIB vise à surmonter les limites de l'architecture actuelle du Métavers (AIB-Metaverse) en introduisant une couche Human-in-the-Loop AI et en modifiant la fonctionnalité des couches d'interaction et de prise de décision afin d'atteindre une intelligence collective issue de la synergie entre l'intelligence humaine et l'intelligence artificielle. Tout d'abord, la couche d'interaction facilite la coordination entre agents en collectant des données des utilisateurs et de l'environnement à travers la stigmergie étendue, où les agents IA laissent des traces numériques interprétables par d'autres agents pour ajuster dynamiquement leurs comportements. Ensuite, la couche interactive Human-in-the-Loop AI joue un rôle fondamental de médiation en analysant en temps réel les interactions entre humains et agents autonomes, permettant ainsi aux décisions des agents d'être affinées grâce aux retours utilisateurs. Enfin, la couche de décision intelligente constitue le noyau du système, où les InSCs orchestrent ces interactions en intégrant des modèles d'apprentissage évolutifs, assurant ainsi une adaptation continue du Métavers aux dynamiques environnementales et aux besoins humains. En combinant ces trois couches, HAIB transforme l'approche actuelle du Métavers en un écosystème intelligent et décentralisé, où humains et IA collaborent de manière fluide et optimisée pour une interaction plus efficace et autonome.

Les expériences menées dans le cadre de cette recherche démontrent l'efficacité du modèle proposé en termes d'optimisation des ressources et d'adaptabilité. Plus précisément, l'implémentation des InSC permet une réduction de la consommation de gaz de 32 à 33 %, un facteur essentiel pour améliorer l'efficience des transactions dans un environnement blockchain, où les coûts énergétiques liés aux contrats intelligents constituent une problématique majeure. Par ailleurs, les résultats montrent une augmentation significative des récompenses cumulées obtenues par les agents IA, ce qui atteste de l'amélioration de leur prise de décision et de leur efficacité dans l'exécution des contrats intelligents. Ces avancées ouvrent la voie à une nouvelle génération de contrats intelligents intelligents, capables d'optimiser leurs stratégies d'interaction de manière autonome tout en s'adaptant aux évolutions de l'environnement.

En intégrant l'IA et la blockchain dans une approche unifiée, cette thèse contribue à l'essor d'un Métavers intelligent, où la gestion des ressources numériques, la prise de décision décentralisée et la collaboration multi-agents atteignent un niveau inédit d'efficacité. Les implications de ces travaux sont vastes et touchent divers domaines d'application, notamment la finance décentralisée (DeFi), où les InSC peuvent améliorer la gestion des actifs numériques et l’exécution des transactions, ou encore le secteur de la logistique intelligente, où la coordination des agents autonomes pourrait être optimisée grâce aux principes de stigmergie étendue. De plus, ces avancées ouvrent des perspectives prometteuses pour la gouvernance du Métavers, en permettant la mise en place de systèmes d’autonomie collective où humains et IA collaborent de manière fluide et transparente.

Abstract

The convergence of 6G and Web 3 technologies with the Metaverse necessitates user-centric, intelligent solutions to address challenges of adaptability, scalability, and efficiency in decentralized systems. This research introduces the Human-AI Blockchain (HAIB) Metaverse architecture and the Intelligent Smart Contract (InSC) framework, which integrate Reinforcement Learning (RL) and extended stigmergy to optimize multi-agent interactions and enable dynamic, self-executing smart contracts. The HAIB architecture enhances human-AI collaboration through a human-in-the-loop approach, facilitating adaptive decision-making and efficient resource allocation. Serving as the cognitive core, the InSC framework combines dynamic environmental feedback with real-time data analytics to enable intelligent decision-making. Experimental evaluations demonstrate that the proposed framework reduces gas consumption by 32–33% while increasing cumulative rewards. These findings highlight the significant potential of intelligent smart contracts in advancing decentralized intelligence within the Metaverse.

Keywords: Blockchain, Extended Stigmergy, HAIB-Metaverse Architecture, Intelligent Smart Contract, Reinforcement Learning Algorithms, Web 3.

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Chapter 1

Introduction

1.1. Motivation and Research Gap

The ongoing evolution of next-generation communication technologies is transforming how digital ecosystems are designed and implemented. Among these advancements, the integration of edge computing, distributed sensing, and AI-driven networks is laying the groundwork for more responsive and intelligent systems. These technologies are enabling applications such as human activity recognition and Vehicle-to-Everything (V2X) communication by supporting real-time, context-aware data processing at the network edge. One significant direction involves the development of AI-native networks, which combine low-latency computing, task-oriented communication, and adaptive learning. These capabilities are particularly relevant to the Metaverse, where immersive experiences and decentralized decision-making require seamless integration of communication, computation, and intelligence [1][2].

While various international organizations such as ITU-R, 3GPP, ETSI, and NGMN Alliance are advancing the broader vision of future communication networks, the emphasis of this thesis lies in how such enabling technologies support human-AI collaboration in decentralized environments like the Metaverse.

The Metaverse represents an emerging next-generation Internet architecture, offering an immersive virtual world that mirrors the physical realm. It encompasses a wide range of economic and social activities, allowing users to engage in interactions similar to those in the real world. This evolving environment enables social interactions through advanced Extended Reality (XR) and Human-Computer Interaction (HCI) technologies, powered by innovations such as Artificial Intelligence (AI) and blockchain.

The Metaverse brings together diverse media types and processes vast amounts of data to ensure user safety and accessibility [3][4]. By 2040, experts predict that the Metaverse will be fully integrated into daily life, serving as an extension of cyberspace with a user-centric and data-driven foundation[5]. However, despite its potential, the current Metaverse architectures face major limitations in terms of adaptability, scalability, user-centric, and intelligent decision-making.

Moreover, executing smart contracts on blockchain platforms incurs high gas fees, increasing the cost of on-chain computations. As the Metaverse expands, the frequency and complexity of smart contract executions will grow exponentially, making traditional blockchain-based interactions inefficient and economically unfeasible. Current approaches fail to address these limitations effectively, highlighting the need for more intelligent, adaptive, and cost-efficient smart contract mechanisms.

To overcome these limitations, this research introduces the Human-AI Blockchain (HAIB) Metaverse architecture, an innovative framework that integrates AI, human intelligence, and extended stigmergy to create an adaptive, intelligent, and scalable decentralized ecosystem.

At the core of the Metaverse's economic system is blockchain, which addresses challenges related to virtual assets and identities, offering users a wealth of consumption opportunities. Integrating blockchain technology will be pivotal in instilling trust, ensuring security, and offering fault tolerance in 6G networks. Blockchain's application will extend to various domains, including network management and resource sharing. In sectors like retail, the Metaverse has the potential to revolutionize customer engagement, communication, and design services. Blockchain-based smart contract mechanisms efficiently manage interactions between digital content creators and users as self-executing contracts that encode agreement terms directly into lines of code, enabling secure and transparent execution of agreements. Practical applications often integrate smart contracts with AI, IoT (Internet of Things) devices, and other technologies to process data and make informed decisions [6]. Recent advancements in smart contracts highlight their ability to automate and secure critical processes, enhance data quality, and protect resources. However, existing smart contracts lack advanced intelligence and adaptability [7] which significantly limits their application in highly interactive and evolving Metaverse environments.

This research proposes an Intelligent Smart Contracts (InSCs) framework by integrating AI and an extended stigmergy mechanism, along with off-chain computation strategies, to enhance the efficiency, adaptability, and economic viability of smart contracts in the Metaverse.

Positioned as the evolutionary leap beyond the mobile Internet era, the Metaverse is a top-level hierarchy of continuous virtual spaces that can integrate with real life, enabling social, commercial, and personal experiences through Web 3 technologies [8]. Web 3 is blockchain-based Internet, the next generation Internet infrastructure, that empowers participants to control their data and make decentralized decisions, fostering a participatory economy, with tokens being central to facilitating transactions and incentivizing participation within decentralized ecosystems [9].

As illustrated in Figure 1.1, the evolution from Web2 to Web3 transforms user interactions from centralized, static models to decentralized, dynamic environments. Web2 emphasizes read-write capabilities, enabling users to consume, generate, and modify content [10]. Platforms like Instagram, Facebook, and Twitter exemplify this by allowing users to publish photos, videos, and text, while others respond through comments or likes. Wikipedia further illustrates collaboration, permitting users to edit and expand each other's contributions. These Web2 platforms utilize conventional stigmergy mechanisms, where indirect communication fosters collaboration among users. Stigmergy, derived from the collective behaviors of social insects like bees and ants, is a decentralized coordination mechanism based on environmental modifications.

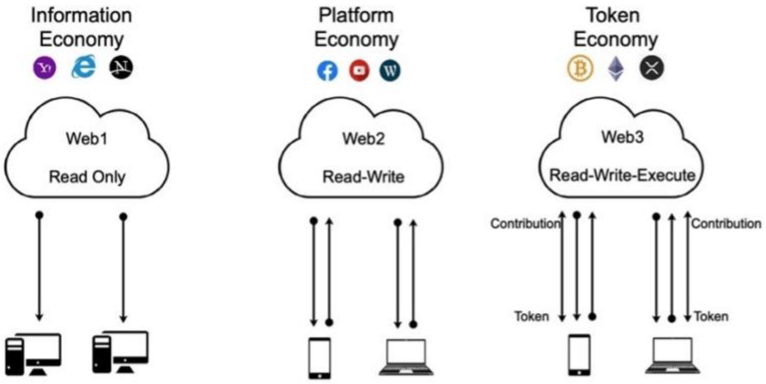

Figure 1.1: The evolution of the Internet from Web1 to Web3 [10].

In traditional stigmergy, agents leave digital pheromones as markers that influence subsequent actions, promoting collaboration among agents within swarm intelligence systems. On Web2 platforms, users leave traces such as posts, edits, or likes, allowing others to react, similar to how ants and bees respond to pheromone trails. For instance, an Instagram post serves as a digital trace that prompts user interactions, while edits on Wikipedia create a continuously revised shared content pool. This indirect communication enables collaboration like interactions observed in social insect colonies, where individuals build upon environmental changes left by others.

Despite these collaborative features, Web2's centralized architecture limits user control over data and scalability. Web3 addresses these limitations by introducing read-write-execute capabilities. Powered by blockchain technologies and smart contracts, Web3 offers a decentralized infrastructure that allows users not only to interact with content but also to autonomously execute transactions and agreements through code [8]. While the introduction of smart contracts signifies a pivotal shift in how the stigmergy mechanism can be applied, it is crucial to note that traditional smart contracts are passive; they execute predefined conditions but do not modify the environment or engage with traces left by other agents. In contrast to Web2, where digital traces are static and require manual interpretation, Web3 enables automated, decentralized interactions, leading to a more sophisticated form of stigmergy known as extended stigmergy. Extended stigmergy enhances traditional stigmergy by incorporating a dynamic medium that autonomously adapts to environmental changes, altering the traces. This enables intelligent smart contracts driven by AI to respond adaptively an advancement beyond the passive nature of conventional agents in Web2, without human intervention. However, for extended stigmergy to occur, smart contracts must evolve beyond their conventional role. They need to be designed to interact with the environment actively, dynamically alter digital traces, and engage with agents in real-time, akin to how social insects modify their surroundings.

As discussed in [11], realizing the Metaverse necessitates addressing three core requirements: cloning real-world objects into virtual environments, self-managing virtual spaces, and ensuring trust and authenticity in virtual transactions. This initiative relies on AI-enabled solutions, including Machine Learning (ML), Deep Learning (DL), and Federated Learning (FL), for managing complex interactions and configurations within the Metaverse. The recently proposed AIB-Metaverse architecture for Web 3, integrates the Metaverse with two pivotal technologies: AI and blockchain. The AIB-Metaverse introduced a virtual environment where users can interact, create, and transact in an immersive and decentralized manner. AI plays a crucial role as the cognitive backbone of the AIB-Metaverse, enabling intelligent decision-making and personalized experiences for users by analyzing data and interactions. Blockchain technology, on the other hand, ensures the integrity and security of data within the AIB-Metaverse, enabling decentralized data storage and ownership without reliance on centralized entities. This addition of AI and blockchain technologies in the AIB-

Metaverse aims to enhance user experiences, ensure data security, and promote decentralization [12]. However, current architectures don't have systems for decentralized collective intelligence, which means that users and AI can't effectively communicate, learn from each other, or work together to improve decision-making. Collective Intelligence (CI) refers to the enhanced capacity that emerges from the collaboration and shared efforts of humans and machines, enabling smarter outcomes than either could achieve alone. These challenges highlight the need for an advanced architecture that integrates human intelligence, adaptive AI, and decentralized decision-making. This would create a more intelligent, responsive, and scalable Metaverse ecosystem.

In this research, we focus on extended stigmergy within a dynamic Metaverse by proposing intelligent smart contracts and AI agents based on RL. Our framework aims to create a human-AI interaction system where AI agents autonomously learn to adapt and optimize interactions. Operating within a decentralized Metaverse, these agents will utilize extended stigmergy to facilitate indirect communication and collaboration among users, agents, and smart contracts, fostering a more efficient, responsive, and intelligent environment.

1.2. Research Objectives and Contributions

The primary objective of this research is to develop an advanced HAIB Metaverse architecture that integrates AI, Human Intelligence (HI), and extended stigmergy to enable intelligent, self-organizing, and decentralized interactions, along with optimizing gas fees. Additionally, the proposed framework aims to address the limitations of current smart contracts, which are often static and lack autonomous decision-making capabilities.

In line with the need for AI-driven self-configuring and self-managing capabilities, and in alignment with the discussion in [5] regarding the importance of human-centric over data-centric services for enhancing user experience in the Metaverse, we propose the HAIB architecture as a user-centric framework that enhances collaboration between humans and intelligent agents, ensuring a seamless, self-managing, and secure Metaverse environment. Unlike the AIB-Metaverse architecture, which primarily relies on AI, HAIB represents a significant advancement by integrating human intelligence with AI to achieve Collective Intelligence (CI). Central to proposed architecture is the human-in-the-loop/AI interactive layer, which establishes a seamless interface between human expertise and AI capabilities, facilitating robust interactions that exceed traditional boundaries. Figure 1.2 illustrates how the

Human-in-the-Loop/AI interactive layer integrates human input, RL agents, and extended stigmergic agents. This fosters adaptive decision-making and enables intelligent contracts that dynamically respond to user interactions and environmental changes while ensuring seamless coordination between agents across online and offline, as well as virtual and physical realms.

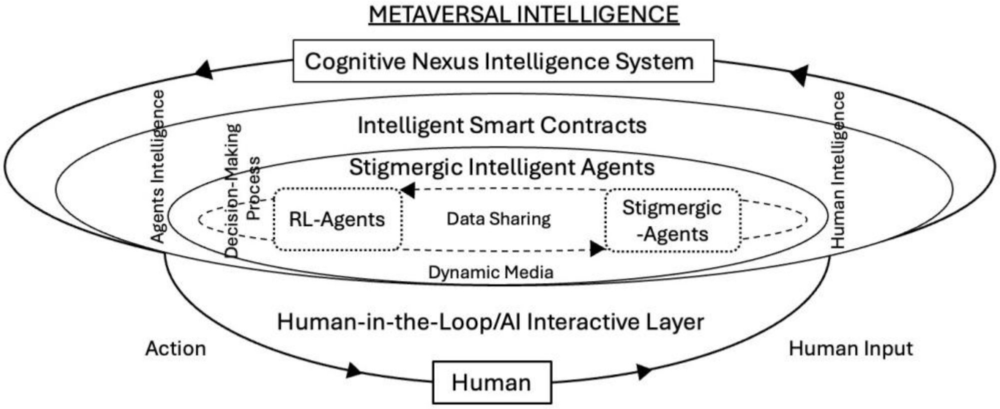

Figure 1.2: Human Interaction with Multi-Intelligence Schemes via Proposed Human-in-the-Loop/AI Interactive Layer

We aim to proposed next generation of smart contracts such that they won't just be smarter, they will become intelligent. This means they will not only execute automatically based on written code and instructions but also capable for self-decision making intelligently, data analysis, and adaptive responses based on real-time information by involving AI, human input, and external data resources like rules. Collectively, these elements form what we refer to as "Metaversal Intelligence". Metaversal intelligence serves as an umbrella term encompassing various intelligent schemes designed to facilitate advanced interaction and decision-making within the Metaverse. These schemes are outlined below:

- **Artificial Intelligence:** AI plays a crucial role in Metaversal intelligence by utilizing specific algorithms to emulate human intelligence. One such algorithm is Reinforcement Learning (RL), which enables agents to learn to navigate and make decisions within an environment to maximize cumulative rewards. In the first step, we employ RL agents, which are well-suited for dynamic environments like the Metaverse due to their ability to adapt to changing conditions and real-time interactions. However, these intelligent agents often require enhancements or hybrid approaches to effectively manage the complexity and variability inherent in such environments[13].

- **Intelligent Extended Stigmergic Agents:** In the second step, we enhance conventional RL agents with extended stigmergy mechanisms, enabling them to dynamically modulate behaviors in response to user interactions, environmental changes, and situational triggers. Unlike traditional RL agents, intelligent extended stigmergic agents autonomously execute adaptive actions aligned with the evolving context, making them highly effective in collaborative, dynamic Multi-Agent Systems (MAS) within Metaverse frameworks. Guided by principles of extended stigmergic self-organization, these agents use decentralized control, where simple individual behaviors collectively yield diverse responses to changing conditions. This approach represents an optimal model for decentralized, self-organizing systems, providing a scalable and generalizable foundation for achieving complex, coordinated behaviors across adaptive multi-agent ecosystems [14][15].

- **Intelligent Smart Contracts (InSCs):** In this step, we incorporate intelligent extended stigmergic agents (combination of RL and extended stigmergy) into traditional contracts. This integration enables agents to operate efficiently by leveraging the intelligent decision-making capabilities provided by RL and the adaptive, self-executing nature of extended stigmergy. These contracts establish rules, conditions, and incentives for agent behavior, thereby promoting more effective coordination among agents. Unlike traditional contracts, InSCs can learn adaptively from interactions and adjust their terms in real-time, offering a dynamic platform for agents to navigate the complexities of the Metaverse.

- **Human Intelligence (HI):** The last step aims to provide a cognitive nexus intelligence system to enhance overall intelligence and adaptability by encompassing the cognitive capabilities and decision-making skills that humans bring to the Metaverse, ensuring that AI systems are aligned with human values and objectives. This interaction between human users and RL agents fosters a collaborative environment where both can learn from each other and improve their effectiveness.

To achieve them, this research is structured around the following four key objectives:

1. Developing the HAIB-Metaverse Architecture
    - Introducing the Human-in-the-Loop AI interactive layer and enhancing the functionality of the interaction and smart decision-making layers to improve adaptability and intelligence in blockchain-based Metaverse architectures.

    - Establishing a collaborative ecosystem where human expertise guides AI-driven agents, ensuring an optimal balance between automation, adaptability, and user control.
2. Proposing the InSCs framework by using RL and extended stigmergy mechanisms to enhance smart contract intelligence.
3. Optimizing gas consumption by implementing an on-chain/off-chain execution strategy
4. Achieving Metaversal Intelligence in a Multi-Agent System
    - Develop a multi-agent decision-making framework, where extended stigmergic AI agents dynamically interact with humans and other autonomous systems in the Metaverse.

By addressing these objectives, this research aims to bridge the gap between AI-driven automation, human-in-the-loop interaction, and decentralized blockchain governance, paving the way for a scalable, adaptive, and cost-efficient Metaverse ecosystem.

In summary, this research contributes to the advancement of intelligent, decentralized Metaverse infrastructures by integrating human-in-the-loop AI, blockchain-based smart contracts, and multi-agent extended stigmergic learning mechanisms. The main contributions of this work include:

1. Introduction of InSCs that leverage RL and extended stigmergy, enabling adaptive, dynamic contract execution based on real-time interactions.
2. Development of the HAIB-Metaverse architecture, incorporating AI, HI, and extended stigmergy mechanism to enhance collaborative intelligence in decentralized environments.
3. Implementation of a hybrid on-chain/off-chain execution strategy, reducing gas fees by 32-33%, minimizing blockchain congestion, and improving transaction scalability.
4. Establishment of a Metaversal Intelligence framework, enabling a self-organizing, multi-agent decision-making ecosystem where AI, blockchain, and HI collaboratively optimize interactions.

1.3. Thesis Outline

The rest of this thesis is organized as follows.

Chapter 2 presents the background and related works of the thesis and explores the emerging Metaverse, tracing its evolution from the AIB-Metaverse to the integration of intelligent smart contracts and extended stigmergic agents. Chapter 3 focuses on advancing the intelligence of smart contracts and introduces the InSC framework, presenting the next generation of contracts. Chapter 4 introduces the HAIB-Metaverse architecture, highlighting the efficiency of using the Human-in-the-Loop AI Interactive layer and emphasizing the development of intelligent extended stigmergic agents. Chapter 5 concludes the thesis with a summary of the findings and outlines potential future work. Finally, Chapter 6 presents the publications related to this thesis.

Chapter 2

Background and Related Work

This chapter provides the foundational context and critical review of existing research relevant to the development of intelligent, human-centric systems in the Metaverse. It serves two primary objectives: (1) to introduce the core concepts and enabling technologies that used the proposed HAIB Metaverse architecture and InSC framework, and (2) to analyze the state of the art in Metaverse-related research, identifying the key advancements, limitations, and research gaps that motivate this thesis.

2.1. Fundamental Principles and Building Blocks

The realization of a scalable, intelligent, and decentralized Metaverse requires a strong foundation built on emerging technologies that enable trust less automation, adaptive intelligence, and decentralized coordination. This chapter explores the fundamental principles that form the theoretical basis of the proposed Human-in-the-Loop AI Blockchain (HAIB) Metaverse architecture. These principles are:

1. Metaverse architecture
2. Blockchain and smart contracts
3. Artificial intelligence
4. Extended stigmergy mechanism

2.1.1. Metaverse Architecture

The structural and functional design of virtual environments, defining how users, AI agents, and smart contracts interact. The Metaverse is a persistent, interconnected, and immersive digital ecosystem where users, AI-driven agents, and smart contracts interact within virtual environments. Unlike traditional online platforms, the Metaverse is envisioned as a decentralized and autonomous system that operates without reliance on a single entity.

As outlined in the previous chapter, the evolution of the Metaverse can be categorized into three key phases:

1. Web 1 → Web 2 (Centralized Interaction): Early digital platforms were centralized, offering static user experiences with limited interactivity.

2. Web 2 → Web 3 (Decentralized Digital Economies): Blockchain introduced decentralized asset ownership, tokenization, and trust less transactions.
3. Web 3 → AI-Driven Metaverse (Autonomous and Intelligent Systems): The future Metaverse aims to integrate AI-driven decision-making, smart contract automation, and self-adaptive multi-agent systems.

2.1.2. Blockchain and Smart Contracts

Blockchain serves as the backbone of decentralized systems, providing tamper-proof, trust less, and verifiable transactions. It ensures:

- Decentralization: Transactions are validated by multiple nodes rather than a central entity.
- Transparency and Security: Data is immutable, preventing unauthorized modifications.
- Automation via Smart Contracts: Contracts execute transactions based on predefined rules.

In this thesis, the Ethereum blockchain is selected as the foundational platform for implementing and evaluating the intelligent smart contract system.

2.1.3. Artificial Intelligence

The adaptive learning mechanism enabling AI-driven decision-making within multi-agent Metaverse systems. RL is a subset of machine learning where an agent interacts with its environment to learn an optimal decision-making policy. The key elements of RL include:

1. Agent: The AI-driven decision-maker (e.g., a smart contract). In this research agents capture and process data from blockchain transactions, smart contract executions, and user interactions. Applications such as Remix (for deploying and managing smart contracts) and MetaMask facilitate these interactions by providing an interface between users and the blockchain network. The details of these applications and their role in interacting with agents are discussed in Section 3.
2. State: The current environment conditions affecting the agent’s actions.
3. Actions: The set of possible decisions the agent can take.
4. Reward Function: A feedback mechanism guiding the agent toward optimal decisions. More details are discussed in Section 3.

By integrating RL into blockchain-based systems, smart contracts can:

- Dynamically optimize gas consumption by selecting cost-efficient execution paths.
- Learn from past transactions to improve efficiency in multi-agent interactions.
- Enhance scalability by adapting execution strategies based on real-time user behavior.

2.1.4. Extended Stigmergy mechanism

Extended stigmergy enables self-organizing behavior in decentralized AI systems by allowing smart contracts and AI agents to:

- Leave and interpret digital traces on the blockchain, influencing other agents' decisions.
- Adapt execution logic based on stigmergic signals rather than fixed rules.
- Facilitate decentralized collaboration between multiple AI-driven agents.

This research integrates extended stigmergy with RL to enhance multi-agent coordination in the Metaverse. The application of stigmergy in InSCs and the HAIB Metaverse is discussed in Chapter 3.

2.2. Literature Review

In this subsection, we begin by reviewing recent progress in the Metaverse and then provide a brief description of the current Metaverse architecture (AIB-Metaverse). Subsequently, we examine the current state of the art and recent advancements in smart contracts, highlighting their limitations and the transition towards intelligent smart contracts. Finally, we explore the evolution of smart contracts into extended stigmergic agents within dynamic media environments.

2.2.1. Emerging Metaverse: Recent Progress and State of the Art

Recently, much progress has been made on many important aspects of the Metaverse. Pertinent publications can be categorized into different areas. Specifically, the areas covered include architecture design, use cases, security, educational technology, and healthcare. The following comprehensive overview serves as a roadmap for navigating the diverse landscape of Metaverse research.

Several seminal contributions have redefined how virtual environments are structured and managed in architectural design. Notably, Decentralized Science (DeSci) Meta-Markets were introduced as a revolutionary concept that enables virtual representations of decentralized science markets. These Meta-Markets serve as platforms for knowledge distribution, bridging the gap between humans, robots, and digital entities. Furthermore, DeMana, a management framework within Meta-Markets, optimizes decision-making processes by facilitating efficient resource allocation and improved knowledge management. Integrating virtual and real markets holds tremendous potential for strategic optimization and efficient resource utilization.

More specifically, the authors of [16] extensively explore collaborative sensing, edge-assisted rendering, and the allocation of resources within the context of developing virtual cities. Similarly, in [17], the authors introduce a Metaverse framework empowered by digital twin technology that seamlessly integrates IoT, XR, and blockchain components to create a comprehensive and immersive experiential realm. The authors of [18] delve into optimizing user incentives within the Ethereum network, aligning contributions with incentivization strategies to elevate service quality. This intricate interplay between the discipline of architectural design and various other facets of Metaverse investigation weaves together a multifaceted narrative that calls for in-depth examination.

In [19], the authors initiate a web evolution beyond Web 2, presenting an AIB-Metaverse-based Web 3 architecture that seamlessly blends physical and virtual worlds. The presented design includes layers for interaction, space rendering, smart decision, and secure storage. Enabling decentralization, AI-driven decisions, and secure blockchain data custody helps advance decentralized intelligence. Further, the authors of [20] address challenges related to splitting XR traffic over 5G networks. They propose power-saving strategies for XR devices that optimize the latency of XR experiences.

As surveyed in [21], emerging Metaverse communication technology and media are continuously advancing. For illustration, Figure 2.1 shows that electronic communication has overcome temporal and spatial limits, resulting in improved information exchange efficiency. The Metaverse's emergence further magnifies this transformation by blending reality and virtuality seamlessly, thus reshaping our perception of time and space.

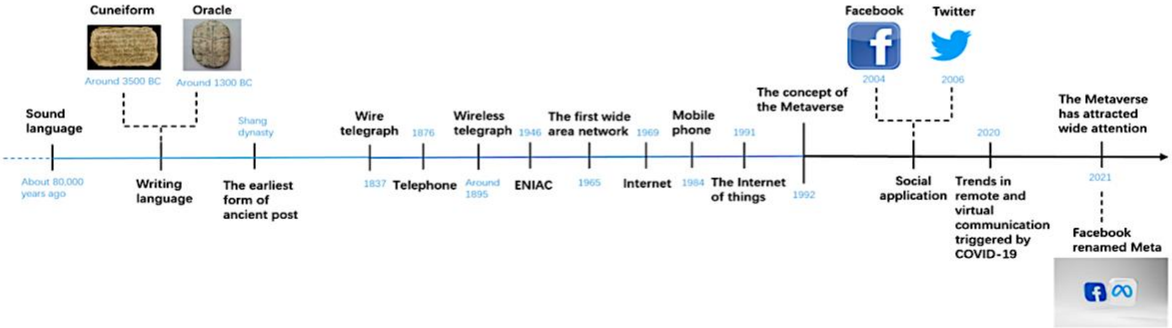

Figure 2.1: Timeline of the development of communication methods [21].

In [22], uncertainty modeling for control engineering tools in Industrial Cyber-Physical Metaverse Smart Manufacturing Systems (ICPMSMSs) is described in more detail. The proposed approach involves decision matrices, estimation methods, and ranking tools for effective tool selection in complex systems. It provides a structured framework for evaluating tools. In [23], a framework is proposed to optimize accuracy and latency in edge intelligence for immersive multimedia applications. By integrating predictive models, deep reinforcement learning, and meta-learning, the framework enhances content delivery, user interaction, and communication latency, thus improving overall application performance.

By analyzing blockchain cryptocurrency networks, the authors of [24] introduce the SVRP method that captures network structural identity using random walks. This method advances representation learning for intricate BCNs. In [25], the focus is on Metaverse xURLLC services in wireless networks. The authors introduce models and contract designs to optimize user experience and utility. This is achieved through strategic resource allocation that enhances both quality of experience and utility. Moreover, the authors of [26] address resource allocation in MEC-enabled Metaverse environments using cooperative multi-agent game theory. The article introduces Dec-POMDP and reward functions to optimize allocation to improve user QoE and resource balance in the Metaverse.

The application domains of the Metaverse, often referred to as its use cases, have captured the attention of researchers seeking to harness its transformative potential. In this context, the authors of [27] investigate the mediatization-metaverse relationship, offering an intricate analysis of value generation and structured interactions in this emergent landscape. Furthermore, in [28], the authors examine the integration of 6G networks into the Metaverse, aiming to elevate vertical industries and immersive experiences. The work in [29] extensively explores communication and networking technologies for real-time interactions in the Metaverse and discusses how the Metaverse evolves with technologies like Blockchain and 6G.

In [30], the authors highlight the integration of pivotal technologies, including digital twins, AI, edge computing, and 5G/6G, within the context of Industry 5.0 advancements. This integration leads to the emergence of an industrial Metaverse, a virtual counterpart running parallel to the physical industrial system. Within this virtual space, global experts collaborate on comprehensive product planning with a transformative impact on conventional manufacturing methods, enhancing productivity and promoting iterative advancement. Figure 2.2 visually outlines the technological progression of the industrial Metaverse for advanced manufacturing. Interestingly, the role of non-fungible tokens (NFTs) in smart cities is further examined in [31], where the authors present innovative solutions for enhancing efficiency, security, and transparency.

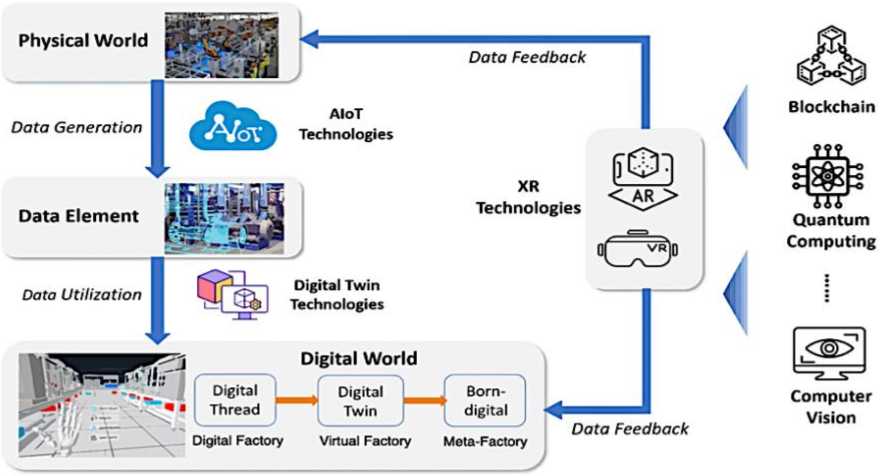

Figure 2.2: Technology roadmap of the industrial Metaverse for advanced manufacturing [30].

Addressing security concerns remains important in the Metaverse ecosystem, prompting researchers to pioneer solutions that protect its participants. The study in [32] meticulously scrutinizes security vulnerabilities in NFT trading platforms, shedding light on plausible attack vectors and proposing remedies to enable security. In a complementary manner, the study in [33] introduces an NFT Private protocol that leverages cryptographic commitments and zeroknowledge proofs to uphold the privacy and confidentiality of NFT transactions. In [34], the authors also tackle essential aspects of continual authentication through federated learning using an adaptable security framework tailored to virtual reality. Similarly, the authors of [35] outline a two-factor authentication model tailored for Metaverse avatars, which assures traceability and consistency of identity.

Other important aspects related to educational technology in the Metaverse have been covered in [36], [37], [38], and [39], where authors explore innovative approaches using technology to enhance learning. In [36], an Edu-Metaverse powered by AI, AR, and blockchain is introduced, focusing on embodied cognition and learner engagement. Similarly, the authors of [37] propose a Metaverse for language learning using constructivist principles, exemplified by the Learningverse platform that emphasizes the impact of data collection. This platform is further investigated in [38] as a tool for interactive education that seamlessly integrates avatars, virtual spaces, and networks. The Education Metaverse framework, outlined in [39], prioritizes adaptability across five layers and underscores the role of blockchains in sustainability and user participation.

In healthcare, the Metaverse holds the potential to revolutionize medical practices and patient experiences. Recent scholarly explorations are notably inclined toward harnessing the potential of the Metaverse for addressing prevailing cognitive health challenges. The conceptualization of “Meta-hospitals” and “Meta-laboratories” ingeniously leverages digital twin technology, alongside augmented and virtual reality, to pave the way for remote consultations, automated testing, and analysis. The meticulously designed approach embraces diverse techniques, such as transcranial direct current stimulation, VR-based exercise systems, and AR-enhanced cognitive rehabilitation platforms [40]. In [41], the authors delve into potential applications of the Metaverse in telemedicine, medical education, and more, spotlighting XR, AI, distributed computing, and decentralized ledger technology (DLT). In [42], the authors exploit NFTs to address healthcare challenges, proposing their use in supply chain and patient-centric data management. In [43], the authors also explore how the Metaverse may enhance healthcare services through innovative technologies and approaches.

Each of the publications mentioned above offers insights that collectively contribute to a comprehensive understanding of the evolving Metaverse landscape.

2.2.2. AIB-Metaverse Architecture

Proposing a shift from the current state of the World Wide Web (WWW), AIB-Metaverse introduces an architecture underpinning Web 3. This innovative framework, combining AI and blockchain technologies, aims to overcome the inefficiencies and privacy concerns plaguing the existing WWW while enhancing user experiences [12].

In this architecture, the status of the physical world is captured by a diverse array of sensors, transmitting data to the virtual space for the construction and updating of digital avatars and environments. Concurrently, the virtual space integrates user inputs and real-world data to render scenes in real-time and provide feedback to the physical space, influencing actions in the physical realm. This architecture comprises four layers and a core engine, as depicted in Figure 2.3 When users interact with Web 3 applications (Web 3 typically refers to decentralized technologies, while Web 3 is a more general term for the semantic web, these two terms are used to refer to similar concepts in this context) within the application layer, the space rendering engine retrieves essential data from the secure storage layer and reconstructs 3D environments based on user's past interactions. Throughout user engagement, commands are captured and forwarded to the interactive layer. This layer interacts with users through digital avatars and relays instructions to the space rendering engine. Here, AI models within the smart decision layer update scenes accordingly. Subsequently, the revised scenes are compressed, streamed back to users, and stored in the secure storage layer for future reference.

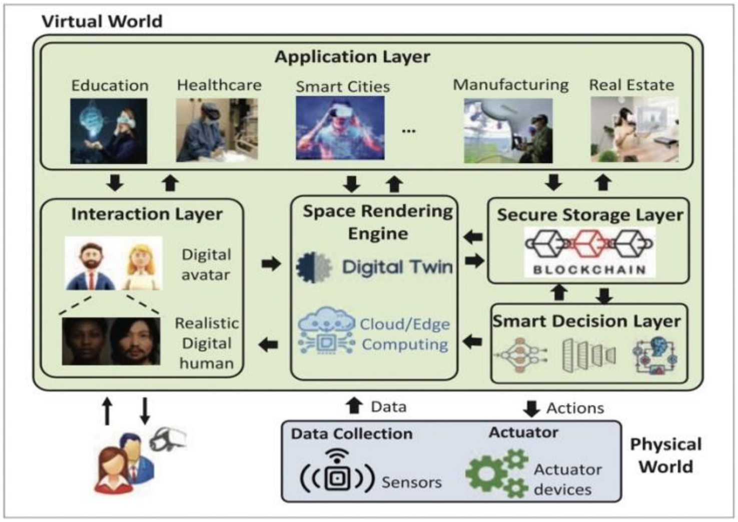

Figure 2.3: The AIB-Metaverse architecture [12].

While this decentralized approach provides trust and enhances user interaction through ubiquitous 3D avatars and autonomous AI operation, it faces significant limitations like users experience limited control over interactions and decision-making processes, restricting flexibility and customization in virtual environments. Also, this system might have trouble quickly adjusting to fast changes or unexpected situations in the Metaverse, making it less effective in a dynamic environment and during real-time interactions. Additionally, focusing too much on autonomous AI can make user experiences less engaging.

To address these challenges, our proposed architecture introduces not only the human-in-the-loop AI interactive layer but also enhances two key layers within the AIB-Metaverse architecture: the interaction layer and the smart decision layer. Inspired by extended stigmergy, the interaction layer enables agents to communicate indirectly through a dynamic medium that evolves and adapts in response to environmental changes. This dynamic medium allows traces to adjust over time, improving the system's ability to share data and experiences. As a result, interactions become more responsive and adaptive, fostering seamless user engagement with an environment that continually evolves based on both agent actions and environmental changes. Simultaneously, we target the smart decision layer, the cognitive core that employs advanced AI models. We aim to introduce extended stigmergy to transform the interaction layer into a dynamic medium capable of adaptation, thereby bridging gaps in adaptability, personalization, and decision-making processes within the current AIB architecture.

2.2.3. State-of-the-Art and Recent Progress on Smart Contracts

In recent years, smart contracts have emerged as a foundational component of blockchain technology, offering programmable contract execution in a secure and decentralized manner since Ethereum's introduction in 2015 [44]. Despite significant progress in understanding and implementing smart contracts, their widespread adoption has brought challenges, particularly in security and adaptability. Traditional vulnerability detection methods have struggled to address diverse solidity versions and comprehensively localize defects across smart contract iterations [45]. Recent advancements, such as machine learning-based approaches like VulHunter and static defect detection tools like SoliDetector, provide more comprehensive vulnerability detection [46][47].

Concurrency control systems like ICOE and SC-CHEF have explored concurrency control techniques to enhance the efficiency and scalability [48][49]. Despite these advancements, current smart contracts still lack adaptability and self-awareness, which limits their ability to dynamically respond to changes in the blockchain ecosystem [50]. Our approach to intelligent smart contracts introduces a novel solution by integrating learning algorithms and dynamic mechanisms. This innovation enables adaptive responses to evolving conditions and overcomes limitations such as deterministic execution and restricted external data integration. These intelligent contracts aim to enhance security and privacy by embedding self-awareness and adaptability, providing a new era of dynamic and responsive contract execution in decentralized environments through advanced AI techniques.

2.2.4. Evolution of Smart Contracts to extended Stigmergic Agents in Dynamic Media

Extended stigmergy introduces a novel coordination mechanism that leverages dynamic media for indirect communication. Unlike conventional stigmergy, where traces in the environment passively influence agent behavior, extended stigmergy enables agents to actively modify and adapt these traces based on intelligent interactions. This is achieved through dynamic media, which are computationally enriched environments capable of processing, storing, and evolving traces in response to agent activities. In the proposed framework of InSC, powered by AI, the dynamic medium is realized through blockchain-integrated platforms. These platforms serve as an adaptive substrate where agents guided by reinforcement learning and extended stigmergic principles update and refine traces. These traces represent collective intelligence, capturing decisions, environmental states, and performance metrics, and are modified in real-time by the agents themselves to optimize interactions and outcomes. The Metaverse, with its inherently dynamic and interactive structure, provides an ideal setting for deploying such systems. The integration of extended stigmergy into intelligent smart contracts enhances the coordination of autonomous agents, enabling efficient decentralized control of complex, adaptive behaviors within this evolving digital ecosystem [51][52].

Unlike static environments, the Metaverse is a multifaceted digital realm characterized by real-time interactions among users and virtual entities across diverse virtual worlds and experiences. This ecosystem hosts a variety of agents, including human users, AI-driven avatars, IoT-connected devices, and autonomous software agents. Each type of agent contributes uniquely to shaping the environment: human users bring creativity and social interaction, AI avatars enable seamless task automation, IoT devices bridge physical and virtual realms, and autonomous agents facilitate decision-making and coordination within the system. Extended stigmergy emerges as a key mechanism enabling indirect interactions among these agents through dynamic, shared media such as blockchain-based smart contracts or decentralized data layers. AI avatars and IoT devices leave data-driven traces, such as updates to a distributed ledger or modifications in a shared virtual workspace. These traces, in turn, inform the actions of other agents without requiring direct communication. Unlike traditional stigmergy, which often relies on simpler environmental signals, extended stigmergy incorporates advanced mechanisms like RL and adaptive algorithms. This allows agents to interpret environmental traces contextually and optimize collective behavior dynamically over time.

The persistent nature of virtual worlds in the Metaverse further amplifies the potential of extended stigmergy. User actions and agent behaviors leave lasting impacts on the environment, such as modifying virtual infrastructure or shaping token economies. These changes generate feedback loops, influencing subsequent decisions and fostering continuous evolution. By decentralizing control over these complex, collective behaviors, extended stigmergy provides a robust framework for ensuring adaptability and scalability within the Metaverse's ever-evolving ecosystem.

The key differences between conventional stigmergy and extended stigmergy can be summarized as follows [14][53]:

- **Passive vs. Active Medium:** In traditional stigmergy, the environment acts as a passive medium, recording traces or signals left by agents without active interpretation. In contrast, extended stigmergy transforms the environment into an active participant, capable of dynamically processing these signals to influence future agent actions. This active medium employs mechanisms such as predictive processing and adaptive feedback loops, enabling it to analyze and interpret traces in real-time. Predictive processing allows the medium to anticipate potential outcomes based on historical patterns, while adaptive feedback loops adjust responses dynamically to reflect ongoing changes in agent behavior and environmental conditions. Together, these mechanisms create a more interactive and responsive MAS, where agents and the environment co-evolve in complexity.

- **Adaptation:** Adaptation in conventional stigmergy is often restricted to static changes in the environment, directly triggered by agent actions, without recognizing or responding to intricate patterns. Extended stigmergy, however, leverages advanced mechanisms such as reinforcement learning, machine learning-based pattern recognition, and probabilistic modeling to enhance adaptability. These mechanisms empower agents to discern trends in the environment and optimize their strategies accordingly. For instance, agents can use RL to iteratively improve decision-making based on reward signals or apply ML to identify and act upon latent patterns in collective behavior. This ability to integrate complex feedback and predictive insights enables extended stigmergy to facilitate intelligent, adaptive coordination in dynamic and heterogeneous systems.

- **Self-Organization:** In conventional stigmergy, self-organization arises from agents' local interactions and modifications to their environment, producing collective behaviors without centralized control. This method is limited to reactive processes where agents respond to immediate changes. Extended stigmergy expands this concept into digital and computational realms, enhancing self-organization through data-driven processes and advanced computational mechanisms. Here, agents interpret and act on digital signals like blockchain updates or distributed ledgers. Extended stigmergy employs predictive analytics, probabilistic reasoning, and multi-layered feedback loops, enabling sophisticated coordination. For instance, agents analyze real-time data to optimize actions based on probabilistic models of future scenarios. This supports emergent, self-organized, and optimized behaviors, making extended stigmergy usable for adaptable and scalable environments like the Metaverse.

- **Trace Diversity:** Extended stigmergy supports heterogeneous traces that vary in type and influence, with effects on agents being context dependent. This results in more nuanced and adaptive behaviors. Conventional stigmergy, on the other hand, relies on uniform and simpler traces (like pheromone trails), leading to localized effects and less flexibility in agent behaviors.

In our recent exploration [54], we examine how extended stigmergy, inspired by the self-organizing behaviors of biological superorganisms, plays a pivotal role in realizing Japan's visionary Society 5.0. A key aspect of this investigation is the creation of tokenized digital twins within decentralized environments. Tokenized digital twins are virtual representations of physical or conceptual entities, enriched with dynamic, tokenized attributes and hosted on blockchain platforms like Ethereum. These digital twins facilitate real-time interaction and coordination among agents by providing a shared, immutable medium for recording states and actions. For example, in dynamic online environments, tokenized digital twins allow agents within Decentralized Autonomous Organizations (DAOs) to interact indirectly through tokenized signals encoded in Ethereum smart contracts. These signals serve as shared digital traces, enabling agents to self-organize and adapt to changes in the system by continuously updating their interactions based on the state of the tokens. By leveraging Ethereum's tokenization capabilities, these environments enable the dynamic integration of human and organizational intelligence, fostering greater adaptability and innovation within DAOs. For more details, refer to [54].

Another interesting example of realizing dynamic environments is Secure and Efficient Stigmergy-Empowered Blockchain (SEB) framework enhances collaborative services on the Internet of Vehicles (IoV) by integrating stigmergy with blockchain technology. Inspired by social insects, stigmergy enables vehicles to communicate indirectly by leaving digital signals, or pheromones, on a blockchain. The blockchain updates based on these pheromones, allowing vehicles to adjust their behavior in real-time. Smart contracts embedded within the blockchain trigger actions or alerts in response to data such as traffic conditions or accidents, facilitating decentralized decision-making and coordination among vehicles. In this framework, vehicles periodically broadcast their status, location, and observations to the blockchain, which other vehicles use to optimize routes, speeds, and overall safety. This creates a self-organizing network that can adapt to real world conditions without central control. SEB utilizes IOTA, a distributed ledger technology specifically designed for the Internet of Things (IoT), to implement its blockchain framework. IOTA's Tangle, a Directed Acyclic Graph (DAG), supports fast and fee-less transactions, ideal for the high frequency, low-latency communication required in IoV scenarios. SEB does not have miners and relies on newly generated transactions to validate previous transactions by incorporating the Transaction Selection for Parent Selection (TSPS) algorithm, which improves transaction validation by selecting parent transactions based on service-attraction value and security needs [55].

In addition to the potential of stigmergy in decentralized systems, AI capabilities further advance the development of intelligent environments by offering robust frameworks, such as RL [56]. There is an increasing demand for effective collaboration mechanisms among intelligent agents, enabling them to achieve collective objectives through continuous learning from the environment based on their individual observations.

Stigmergic Independent Reinforcement Learning (SIRL) addresses this challenge by integrating stigmergy with Multi Agent Reinforcement Learning (MARL). In SIRL, agents use digital pheromones to indirectly influence each other's actions, which helps overcome limitations such as local observation constraints and the non-stationary nature of dynamic environments. To manage conflicts between agents, especially when they are close or their actions overlap, SIRL utilizes neural networks to prioritize tasks, reducing conflicts and enhancing efficiency. Moreover, SIRL employs a federated training approach to optimize each agent's neural network in a decentralized manner, enabling them to learn and adapt without relying on a central controller. By combining these two strategies, stigmergy for guiding large-scale, collective behavior and neural networks for managing local interactions and conflicts, SIRL enhances the ability of agents to work together effectively, even in complex and dynamic environments. Also, SIRL utilizes A3C (Asynchronous Actor-Critic Agents), a MARL technique that improves learning efficiency by allowing multiple agents to learn asynchronously. A3C leverages multiple actor-critic networks that explore different aspects of the environment simultaneously, accelerating the convergence of policies and enhancing the coordination among agents [52].

As mentioned before while traditional smart contracts offer secure and deterministic execution, they lack adaptability and self-awareness in dynamic environments like the Metaverse. By empowering these contracts with extended stigmergic agents and RL, we can overcome these limitations. Like SEB and SIRL frameworks, which integrate effectively stigmergic agents within a blockchain to facilitate adaptive coordination and collaboration, our method combines extended stigmergy-driven communication with RL based on blockchain technology to develop more intelligent and adaptable smart contracts suited for dynamic, decentralized environments. Stigmergic agents utilizing extended stigmergy enable decentralized coordination in dynamic environments by interacting with and modifying their surroundings, thereby influencing the behavior of other agents. In this context, an ”agent” refer to autonomous software entities, such as intelligent smart contracts and extended stigmergic agents, that process and act upon digital traces within a decentralized, dynamic environment. These software agents are capable of learning from and responding to environmental changes through mechanisms like RL and extended stigmergy.

On the other hand, humans operate autonomously within the online environment to achieve system objectives. Users interact with the system by leaving traces (e.g., inputting data or triggering actions), which the agents interpret and act upon. While human input influences the system, the agents remain distinct, autonomously executing tasks and making decisions based on both human traces and other environmental factors.

Chapter 3

Next-Gen Contracts: Advancing Smart Contract Intelligence

The role of intelligent smart contracts is multifaceted and transformative. These dynamic agents are the vital bridge between the digital landscape and human entities coexisting within the Metaverse. Their adaptability and situational awareness drive the flourishing of Metaverse’s forthcoming virtual society within this complex and ever-evolving environment. This transformative perspective elevates smart contracts from static, predefined scripts to dynamic and responsive entities. One of the key innovations in our work is the integration of intelligent extended stigmergic agents alongside smart contracts, thereby introducing a novel dimension to the Metaverse’s digital ecosystem. These agents orchestrate processes, enforce rules, and enable trust less interactions, all while possessing the unique ability to transcend predefined rules. Their agility allows them to function as intelligent agents responsive to the evolving environment, effectively mirroring the adaptability inherent in natural systems.

With regard to the design and challenges of intelligent extended stigmergic agents and smart contracts, this research explores several promising directions:

- Dynamic Contract Evolution: We are exploring methods for smart contracts to adapt and evolve over time, learning from interactions and dynamically updating their rules and behavior to optimize outcomes.

- Enhanced Situational Awareness: Our focus includes enhancing the agents’ ability to perceive and understand the evolving context within the Metaverse, allowing for more informed decision-making and coordination.

- Inter-Agent Communication: Facilitating seamless communication and cooperation among intelligent extended stigmergic agents and smart contracts is critical to our research, promoting the emergence of sophisticated digital ecosystems.

In this section we propose the InSC algorithm to advance smart contracts from executing predefined code to becoming intelligent. As illustrated in Figure 3.1, this multi-agent interaction framework serves as the ”brain” of the HIAB-Metaverse architecture, enabling contracts to autonomously process information and make informed decisions.

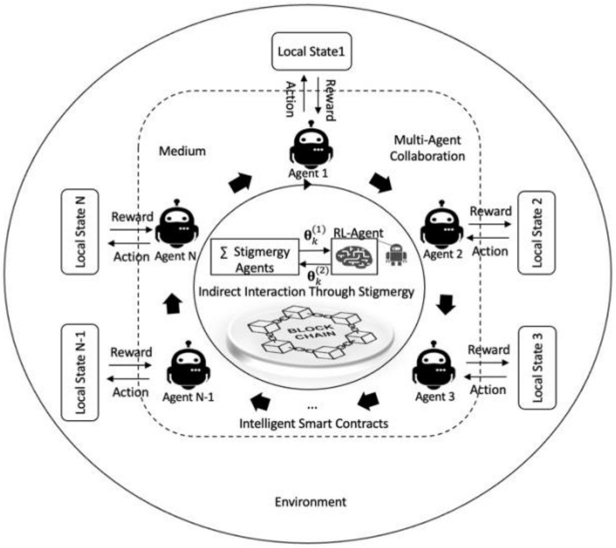

Figure 3.1: The proposed InSC framework

In this framework, human users leave and read digital traces within the environment, such as inputs or interactions in both virtual Metaverse environments and physical world systems. These traces are then acted upon by intelligent agents, extended stigmergic agents empowered by RL, who autonomously automate processes, facilitate self-decision-making, conduct real-time data analysis, and provide adaptive responses as detailed in the following subsections.

3.1. The Convergence of AI and Blockchain

AI refers to a system's ability to independently learn from large datasets by identifying patterns and subsequently making predictions or recommendations, encompassing the processes of perceiving, learning, acting, and adapting. Over time, AI algorithms refine their capabilities by adapting to new data, enhancing their performance and accuracy. The increasing importance of AI in recent years can be attributed to the convergence of three critical factors: the abundance of data, advancements in algorithmic methodologies, and the availability of cost-effective computational power and storage. AI outcomes can be classified into three main categories:

- Descriptive: Providing insights into what has occurred, with AI functioning as an assistant.
- Predictive: Forecasting future events, positioning AI as an advisor.

- Prescriptive: Offering recommendations for action, where AI operates as an agent.

AI's potential lies in its ability to augment human intelligence, a concept often referred to as Intelligence Augmentation. The integration of AI with blockchain technology has the potential to unlock significant synergies, enabling efficiency improvements that are otherwise unattainable. This collaboration can drive innovation across industries, transform business models, and create substantial value in digital transformation initiatives [57].

Blockchain, with its inherent features of immutability, provenance, and robust control mechanisms, complements AI by addressing its key limitations. These include enhancing trust, mitigating privacy concerns, and improving the explain ability of AI's decisions. The integration of AI and blockchain creates new opportunities for building intelligent decentralized systems. Moreover, Amara's Law[1] emphasizes the tendency to overestimate the short-term impacts of a technology while underestimating its long-term effects. While blockchain initially experienced significant hype, and AI has recently emerged from a prolonged "AI winter", their integration offers unprecedented opportunities. The secure and accurate data flow facilitated by blockchain can accelerate and enhance AI systems, leading to faster, more effective decision-making processes and delivering transformative value [57].

3.1.1. Deep Q-learning (DQL) Algorithm

Recent advancements in AI, particularly in RL, have provided promising solutions to challenges in dynamic environments. RL is a branch of machine learning where an agent learns to make decisions through trial and error by interacting with its environment. It has achieved remarkable success in various fields, including strategic games such as Go and StarCraft, as well as in complex scientific problems like protein folding.

At its core, RL involves four key components: policy, reward, value function, and environment model. The policy defines the agent's decision-making behavior, while the reward serves as the reinforcement signal that guides learning. The value function evaluates the long-term quality of a state, and the environment model predicts how the environment responds to actions. RL algorithms can be broadly classified into model-free and model-based approaches. Model-free methods, such as DQL, rely solely on trial-and-error feedback to update policies using value

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[1] https://deviq.com/laws/amaras-law

function estimates, whereas model-based methods leverage an environment model to evaluate state values by simulating future states and actions.

RL operates on the framework of a Markov Decision Process (MDP), which consists of states, actions, and rewards aimed at achieving long-term objectives efficiently. Model-free RL methods, such as DQL, are particularly effective in scenarios where the agent has no prior knowledge of the environment's transition model or reward function. DQL approximates the action-value function Q(s, a), representing the expected cumulative reward for taking action α in state s. These Q-values are stored in a memory and updated iteratively using the Bellman Equation 3.1:

$$Q_i(s,a) \leftarrow Q_i(s,a) + \alpha \cdot (r + \gamma \cdot max_{a'} Q_i(s',a') - Q_i(s,a)) \tag{3.1}$$

where α is the learning rate determining the update magnitude, r is the immediate reward received, γ is the discount factor balancing immediate and future rewards, s′ is the subsequent state, and a′ is the next action.

Agents employing DQL explore and exploit their environment using strategies like epsilon-greedy to learn an optimal policy that maximizes cumulative rewards over time. This process enables agents to map states to actions effectively, making Q-learning particularly suited for environments where prior knowledge is absent.

To enable adaptive decision-making and enhance the responsiveness of intelligent smart contracts, our approach leverages the DQL algorithm, a model-free RL method renowned for its ability to learn optimal actions through experience [56]. Through the HAIB-Metaverse architecture, the InSC enables the utilization of shared states and actions among multiple agents within a decentralized environment. Unlike traditional smart contract systems, which operate on isolated states and actions, this model fosters an environment where agents can collaboratively interact through a common state space, thereby enhancing the adaptability of agents. In the InSC algorithm, structured state and action spaces are defined to guide the decision-making processes of intelligent agents, as outlined below.

- Environment and State Spaces: In the HAIB architecture, the environment for DQL agents is linked to the blockchain ecosystem, leveraging dynamic medium features such as superposition, decay, and diffusion to model the interaction space. Agents operate within a multi-agent smart contract environment, where the state $S(t)$ at each time step reflects the evolving context of the system. This state incorporates several key factors unique to HAIB, including the current phase of the contract (e.g., initialization, validation, execution, or finalization), extended stigmergic traces left by agents and users, and blockchain performance metrics such as gas consumption, transaction throughput, and execution success rates.

Formally, the system state at time t can be expressed as:

$$S(t) = (\phi(t), \tau(t), \mu(t))$$

Where:

- $\phi(t) \in$ {Init, Validation, Execution, Finalization}: the discrete smart contract phase (4 values).
- $\tau(t) \in R^n$: a real-valued vector of stigmergic trace values, where n is the number of trace types or contributing agents (e.g., one value per agent or per type of trace).
- $\mu(t) \in R^m$: a real-valued vector of blockchain performance metrics, where m is the number of metrics tracked (e.g., gas cost, transaction delay, success rate).

Therefore, instead of using tabular representations, the system employs Deep Q-Networks (DQNs) to approximate the action-value function across this continuous and high-dimensional state space. By incorporating superposition, agents can interpret overlapping traces from multiple entities, enabling them to consider collective actions and feedback. Decay ensures that recent interactions are prioritized, allowing the agents to respond dynamically to the most current state of the system. Diffusion helps spread environmental information across the system, facilitating collective intelligence and enhancing coordination among agents. These dynamics enable agents to refine their decision-making processes in real-time, ensuring their actions are aligned with both system-wide goals and user inputs. The shared state space, enriched with these HAIB-specific dynamics, allows agents to collaboratively assess the environment, fostering adaptive behavior, improved coordination, and enhanced efficiency within decentralized ecosystems.

- Actions spaces: The action space in the DQL algorithm for the HAIB architecture is designed to incorporate key operations that agents can undertake to influence the behavior of the smart contract, while reflecting the dynamic medium features of superposition, decay, and diffusion. The action space A(t) includes four primary operations: (1) validate transaction, which transitions the smart contract from the initial state to the validation phase, considering overlapping extended stigmergic traces from multiple agents and users, thereby ensuring robustness in validation; (2) optimize gas, which minimizes transaction costs through efficient resource allocation, while applying decay to prioritize recent transaction states, ensuring relevance in dynamic environments; (3) execute transaction, where the agent applies validated transactions to alter the state of the smart contract, and the outcomes are diffused across the blockchain's shared memory, promoting synchronized decision-making; and (4) audit transactions, which involves reviewing past transactions and leveraging both decay (to prioritize recent anomalies) and superposition (to aggregate multi-agent feedback), ensuring a thorough and intelligent audit process.

the action space be defined as:

$$A = \{a_1, a_2, a_3, a_4\} = \{\text{Validate}, \text{OptimizeGas}, \text{Execute}, \text{Audit}\}$$

Each agent chooses one action per decision step based on its observation of the state S(t). Although these operations correspond to contract phases, the agent's policy determines which operation to apply at each time step, allowing for adaptive optimization.

By systematically defining these states and actions, we ensure that agents can effectively learn and adapt their behaviors, leading to enhanced autonomy and responsiveness in smart contract operations. This capability is further facilitated by the HAIB architecture, where multiple agents collaborate and adapt their behaviors through learned Q-values and extended stigmergy-based shared memory. agent functions as a Q-learning agent designed to interact independently with the smart contract environment and learn optimal actions through trial and error, receiving rewards and penalties specifically tied to blockchain-based outcomes. In the HAIB system, rewards are realized through blockchain tokens, which are granted to agents for actions that contribute to the efficiency and success of the system, such as executing transactions with minimal gas usage, ensuring transaction validation, or optimizing resource allocation. These rewards incentivize agents to align their actions with the overall goals of the smart contract, such as improving transaction throughput or reducing costs.

On the other hand, penalties are applied for actions that lead to inefficiencies, such as excessive gas consumption or failed transactions. These penalties can be realized as token deductions or a reduction in future action rewards, discouraging undesirable behaviors and promoting optimal decision-making. This collaborative learning process not only enhances individual agent performance but also reinforces the overall system's resilience and adaptability by ensuring that agents are driven to improve the decentralized network's operational efficiency and sustainability. Through this mechanism, the HAIB architecture ensures that agents' actions are not only based on learning from their own interactions but are also aligned with collective goals, fostering both individual and system-wide improvements.

The agents leverage a deep Q-network (DQN) to approximate action-value functions and update their policies based on the rewards received from the environment. This allows each agent to autonomously develop strategies to optimize critical smart contract operations such as validation, execution, and gas optimization. The learning process is driven by the agents' local observations of the state space, and decisions are made using an epsilon-greedy strategy to balance exploration and exploitation. The DQL algorithm is crucial here as it allows agents to learn optimal strategies for managing these smart contract states and actions. The state-action pairs are continuously updated in the blockchain through extended stigmergy (This will be elaborated further in the next section), ensuring agents adapt their behavior based on real time data from both the contract and other agents. The main notations used in our mathematical modeling which captures how the state-action spaces defined align with the adaptive, multi-agent behaviors are presented in Table 3.1.

Table 3.1: Parameters and their descriptions

Parameters	Description
γ	Discount factor
ϵ	Exploration rate
β	Stigmergy weight
η	Future q-value weight
α	Learning rate

The essential components of our DQL framework are as follows:

DQN Architecture: In environments with continuous or large action spaces like blockchain, a tabular approach to Q-learning is impractical. Neural networks are powerful function approximators that allow us to generalize Q-values across a broad range of states and actions. Instead of explicitly storing Q-values for every state-action pair, the network approximates the value function based on the input state. This generalization enables the network to apply learned policies to similar, previously unseen states, thus enhancing learning efficiency by leveraging past experiences across diverse states and actions [56]. We define our DQN as a fully connected neural network with these layers:

- The input layer captures state information and maps it to a higher dimensional space (128 units), allowing the network to learn richer representations of the state.
- The two hidden layers, each with 128 units and using the Rectified Linear Unit (ReLU) function, help the network learn complex features from the state representations by facilitating non-linear decision boundaries.
- The output layer produces Q-values for all possible actions, which are then used to determine the optimal action for a given state.

Experience Replay: To stabilize the learning process, we implement experience replay. Each agent stores transitions (state, action, reward, next state, done) in a replay memory buffer. This buffer allows us to sample batches of transitions for training the Q-network, reducing correlation in the training data and improving learning efficiency.

Target Network: To further stabilize training, we use a separate target network that is periodically updated to reflect the policy network's parameters. This target network helps prevent drastic oscillations in Q-value updates and is used to compute the targets for the Q-learning updates as Equation 3.2:

$$y_i = r_i^t + \gamma \cdot \max_a Q_{i'}(s_i^{t+1}, a) \tag{3.2}$$

Here, r_i^t is the immediate reward, γ is the discount factor, and $Q_{i'}(s_i^{t+1}, a)$ determines the predicted Q-value for the next state using the target network.

Each agent maintains its own Q-network and learns by interacting with the environment through Q-learning updates while the target network is used for stable updates of future rewards. The Q-values are updated using Equation 3.3:

$$Q_i(s_i^t, a_i^t) \leftarrow Q_i(s_i^t, a_i^t) + \alpha \left[y_i - Q_i(s_i^t, a_i^t) \right] \tag{3.3}$$

We develop our proposed solution in our proposed HAIB- architecture (next subsection, Figure 5.1). Specifically, the intelligent agents employed in the decision layer are modeled using Equations 3.2 and 3.3 The learning process is facilitated by a target network and experience replay, enabling the agents to optimize their decision-making based on accumulated experiences. This model is essential for agent autonomy, allowing each agent to enhance contract execution through a reward-based system.

We also develop our proposed solution for the concepts of superposition, decay, and diffusion, as illustrated in the human-in-the-loop/AI layer of Figure 4.1 (next subsection), through the agent's probabilistic state-action evaluation.

- Superposition is reflected in the agent's simultaneous consideration of multiple actions, allowing it to evaluate potential outcomes before making a decision.
- Decay is represented by the reduction of the exploration rate ϵ over time, encouraging agents to transition from exploration to exploitation of known optimal actions, thereby enhancing decision-making efficiency.
- Diffusion occurs as agents share knowledge and experiences through interactions, influencing their exploration strategies and helping disseminate effective actions across the group.

This evaluation considers multiple potential actions simultaneously until one is selected based on its Q-value. The process is governed by the exploration-exploitation trade-off in RL, as described by Equation 3.4:

$$\epsilon \leftarrow \max\left(\epsilon_{\min}, \epsilon \times \epsilon_{\text{decay}}\right) \tag{3.4}$$

With probability ϵ, the agent explores by selecting a random action, while with probability 1-ϵ, it exploits by choosing the action with the highest Q-value.

This collaborative learning process ensures that agents not only adapt to their environment but also benefit from the collective experiences of their peers, ultimately enhancing overall system performance.

Also, the loss function is defined using the Mean Squared Error (MSE) between the Q-values predicted by the policy network and the target Q-values. This formula measures how accurately the Q-network estimates the value of actions compared to the target values as Equation 3.5:

$$L(\theta_i) = \frac{1}{|M_i|} \sum_{(s_i^t, a_i^t, r_i^t, s_i^{t+1})} \left[y_i - Q_i(s_i^t, a_i^t) \right]^2 \tag{3.5}$$

Where $L(\theta_i)$ measures how far the predicted Q-values are from the target Q-values, $|M_i|$ is the batch size (number of transitions being averaged over), y_i is the target Q-value, and $Q_i(s^t_i, a^t_i)$ is the predicted Q-value from the policy network for a given state-action pair. By minimizing this loss, the neural network learns to better approximate the Q-values.

3.2. Extended Stigmergy Mechanism

Based on [14], stigmergy mechanism is recognized as an effective strategy for agent coordination and collaboration in dynamic environments, similar to the SIRL [52] and SEB [55] frameworks. However, extended stigmergy goes beyond mere indirect interaction; it enhances the agents' ability to dynamically adapt to both individual and collective experiences by continuously updating their behaviors based on real-time environmental changes. Our goal is to enable extended stigmergic agents to coordinate and collaborate efficiently by incorporating environmental factors, AI, and HI inputs. The proposed ecosystem features discrete local states and agents, which allows multiple agents to perform parallel tasks simultaneously. In this ecosystem, the medium is crucial not only for facilitating efficient extended stigmergic interactions between agents and their environment but also for providing a dynamic platform where agents can modify their behaviors in response to shifting environmental contexts, making the system highly adaptive.

Our mathematical solution for extended stigmergic interaction is modeled by the Equation 3.6.

In this model, environmental traces influence agent behavior through shared memory, integrating individual performance with collective experience. This approach ensures that agents enhance their learning not only from their own actions but also by leveraging the experiences of others, as follows:

$$S_i(s_t^i, a_t^i) \leftarrow S_i(s_t^i, a_t^i) + \beta_{\text{stig}} \left[\alpha_{\text{perf}} \cdot TSR_i + (1 - \alpha_{\text{perf}}) \cdot (Q_i(s_t^i, a_t^i) - S_i(s_t^i, a_t^i)) + \eta_{\text{futureQ}} \cdot \max_{a'} Q_i(s_{t+1}^i, a') \right] \tag{3.6}$$

Where $S_i(a, s)$ is current extended stigmergy value for action a in state s for agent i , β is the extended stigmergy update learning rate, α is weight assigned to Transaction Success Rate (TSR) in the update and controls the balance between performance-based learning and the difference between Q-values and extended stigmergy values , η is influence of future rewards, and $\max_{a'} Q_i(s_i^{t+1}, a')$ represents maximum Q-value for the next state s' over all possible actions a'.

In this formula, TSR_i represents the Transaction Success Rate for agent_i, which quantifies the ratio of successful actions to gas usage, weighted by the complexity of the tasks performed. It is defined in Equation 3.7:

(3.7)

$$TSR_i = \frac{\text{successful actions}}{\text{gas usage}} \times \text{complexity factor}$$

Where:

- Successful Actions: This term refers to the number of operations or transactions completed successfully by the agent, such as validations, contract executions, or token transfers. High success rates are essential in blockchain environments to reduce failed transactions, avoid unnecessary costs, and ensure overall system reliability.
- Gas Usage: This denotes the cumulative computational cost incurred by the agent's actions. In gas-metered blockchain platforms like Ethereum, this directly reflects the transaction cost and resource consumption.
- Complexity Factor: The complexity factor accounts for the operational difficulty, resource intensity, and execution risk associated with each action. It ensures that more computationally expensive and high-impact tasks are weighted more heavily when measuring performance. This factor is computed as a weighted combination of gas cost, latency, and failure risk. It is defined in Equation 3.8:

(3.8)

$$\text{Complexity Factor} = \lambda_1 \cdot \text{GasCost} + \lambda_2 \cdot \text{Latency} + \lambda_3 \cdot \text{Risk}$$

where $\lambda 1$, $\lambda 2$, $\lambda 3$ are tunable coefficients. This design encourages intelligent agents to pursue meaningful, high-efficiency actions while accounting for both task difficulty and system sustainability. In this way, TSRi offers a normalized performance measure that balances operational success with resource optimization in dynamic, multi-agent smart contract systems.

Therefore, we can consider this formula as Equation 3.9:

(3.9)

$$TSR_i = \frac{\sum_{j=1}^{k} w_j \cdot \text{Success}_j}{\text{GasUsed}_i}$$

Where:

- $\text{Success}_j \in \{0,1\}$
- w_j is a complexity factor for action_j
- k is the number of actions
- GasUsed_i is total gas consumed by agent_i

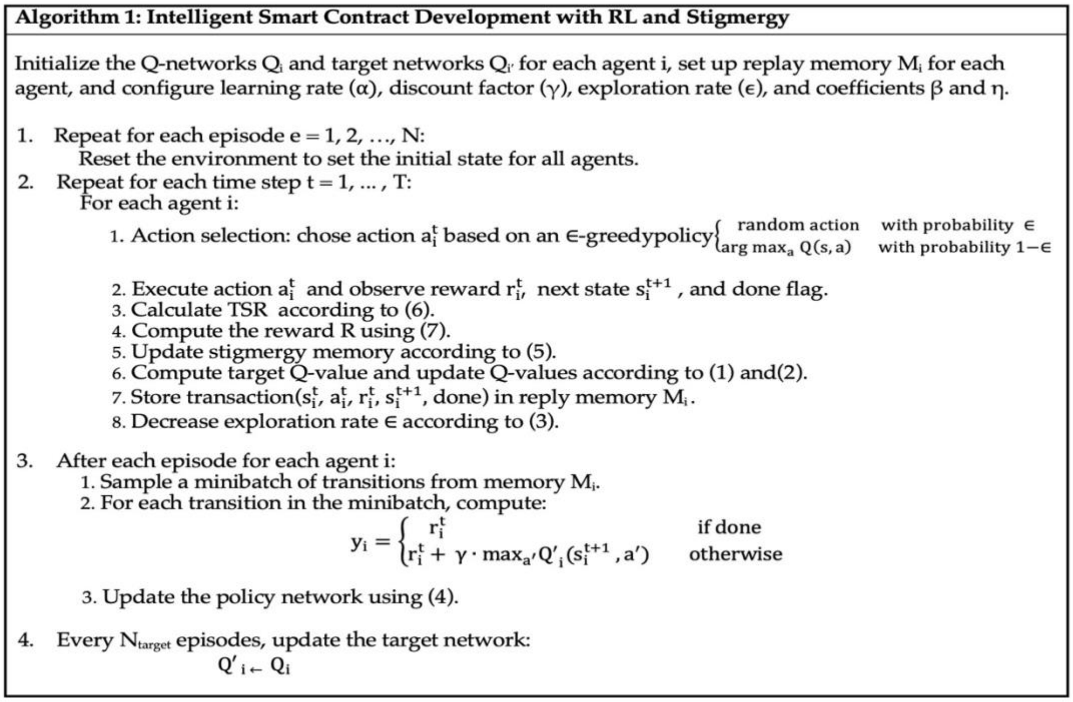
The complexity factor w_j reflects the relative importance or difficulty of executing action j and is used to ensure the TSR metric fairly values more complex operations. It combines gas cost, latency, and execution risk to form a normalized score representing the action's operational weight. This allows the reward system to better reflect not only success frequency but also the contribution of meaningful, high-impact actions.

Extended stigmergy does more than facilitate agent collaboration; it enables agents to make decisions that account for both real-time local interactions and broader, system-wide knowledge, creating a feedback loop that continuously refines contract execution strategies. In this ecosystem, each agent receives an individual reward based on its actions and state transitions. These rewards can be task-specific, including positive rewards for achieving subgoals and negative rewards for undesirable actions. Additionally, in tasks involving collaboration among agents, rewards should be shared among all participating agents when a collective goal is achieved, incorporating extended stigmergy information into individual rewards. To guide the agents' learning process, we determine the total reward at time *T*, calculated as the sum of individual rewards collected at each time step *t* as the agent interacts with the environment. Furthermore, we modeled HI input by integrating it into the decision-making process, which modifies Q-values based on user feedback (human-in-the-loop). This integration is reflected in the adaptive reward system as Equation 3.10:

$$R_{agent}^{t} = \beta \times TSR_{agent}^{t} + \eta \times max_{\,a'}\, Q_{agent}(s', a') - Penalty_{agent}^{t} \qquad (3.10)$$

Where β scales the contribution of TSR, η controls the impact of future rewards, and penalty reduces the reward for incorrect actions.

Extended stigmergy thus directly impacts the learning and adaptability of intelligent smart contracts by continuously feeding real-time environmental data into the decision-making process, empowering agents to modify their behaviors dynamically, optimize resource consumption, and enhance collaboration efficiency. Figure 3.2 illustrates the InSCs algorithm, which integrates the DQL algorithm with extended stigmergy to optimize smart contract execution. By leveraging both learned Q-values and collaborative feedback mechanisms, the algorithm enhances decision-making and adaptability in complex, dynamic Metaverse environment.



```
Algorithm 1: Intelligent Smart Contract Development with RL and Stigmergy

Initialize the Q-networks $Q_i$ and target networks $Q_{i'}$ for each agent i, set up replay memory $M_i$ for each
agent, and configure learning rate ($\alpha$), discount factor ($\gamma$), exploration rate ($\epsilon$), and coefficients $\beta$ and $\eta$.

1. Repeat for each episode $e = 1, 2, \ldots, N$:
     Reset the environment to set the initial state for all agents.
2. Repeat for each time step $t = 1, \ldots, T$:
     For each agent i:
         1. Action selection: chose action $a_i^t$ based on an $\in$-greedypolicy$\begin{cases} \text{random action} & \text{with probability } \in \\ \arg\max_a Q(s,a) & \text{with probability } 1-\in \end{cases}$
         2. Execute action $a_i^t$ and observe reward $r_i^t$, next state $s_i^{t+1}$, and done flag.
         3. Calculate TSR according to (6).
         4. Compute the reward R using (7).
         5. Update stigmergy memory according to (5).
         6. Compute target Q-value and update Q-values according to (1) and(2).
         7. Store transaction($s_i^t$, $a_i^t$, $r_i^t$, $s_i^{t+1}$, done) in reply memory $M_i$.
         8. Decrease exploration rate $\in$ according to (3).
3. After each episode for each agent i:
     1. Sample a minibatch of transitions from memory $M_i$.
     2. For each transition in the minibatch, compute:
          $y_i = \begin{cases} r_i^t & \text{if done} \\ r_i^t + \gamma \cdot \max_{a'} Q'_i(s_i^{t+1}, a') & \text{otherwise} \end{cases}$
     3. Update the policy network using (4).
4. Every $N_{target}$ episodes, update the target network:
          $Q'_i \leftarrow Q_i$
```

Figure 3.2: The proposed InSC algorithm

3.3. Smart Contracts and Agent Interaction Model

In the proposed HAIB-Metaverse architecture (described in the next section), smart contracts function as structured execution environments that interact with intelligent agents. While smart contracts do not perform learning or reasoning themselves, they are designed to facilitate adaptive behavior by exposing well-defined functions that agents can call. These interactions occur in a hybrid on-chain/off-chain system where intelligent agents operate off-chain and communicate with the blockchain through secure interfaces.

3.3.1. Smart Contract Functions and State Design

The smart contracts contain a fixed set of functions representing the discrete actions that RL agents can perform:

- Validate Transaction(): verifies the integrity and structure of a proposed transaction before execution.
- Optimize Gas-Usage(): applies predefined strategies to minimize transaction gas costs during execution.
- Execute Transaction(): finalizes the contract logic based on current validated inputs and triggers the agreed outcomes.
- Log Interaction(): emits minimal trace data (such as action identifiers, timestamps, and resulting state transitions) to the blockchain for transparency and traceability.

The smart contract maintains:

- The current state of the contract (e.g., initialization, validation, execution, finalization).
- Essential environmental variables, such as previously selected actions or current thresholds.
- Event logs (emitted using Solidity events) to signal outcomes of agent interactions.

All of these are stored on-chain, ensuring immutability, verifiability, and decentralized coordination. However, complex learning parameters, cumulative performance metrics, and audit trails are not stored on-chain due to cost and scalability concerns.

3.3.2. On-Chain vs. Off-Chain Responsibilities

Agents operate entirely off-chain and run a DQL algorithm (Algorithm 1). Their decision-making loop follows this cycle:

- Perceiving the current smart contract state and historical traces (by querying on-chain variables or reading emitted events).
- Selecting an optimal action based on their current Q-values.
- Executing the selected action by calling the corresponding smart contract function via a Web3 interface (e.g., Web3.py).
- Receiving feedback from the blockchain (e.g., transaction result, gas used, new state) and update their Q-table accordingly.
- Storing detailed performance logs and audit information off-chain, where computational analysis and learning updates are handled.

In this architecture, the only components that execute on-chain are the smart contract functions explicitly triggered by agents. These include state transitions, execution of logic defined in functions such as Validate Transaction(), Optimize Gas-Usage(), Execute Transaction(), and event emission for trace logging. All such operations are deterministic, stateless computations or state updates that are securely recorded on the blockchain.

This structure ensures that computationally intensive tasks such as learning, reward computation, policy optimization, and historical data analysis, remain off-chain, while the blockchain is leveraged for secure function execution, traceability, and decentralized coordination.

3.3.3. Smart Contracts as Stigmergic Media

The smart contract also functions as a stigmergic medium, enabling indirect communication among agents. Each agent's action such as executing a contract function leaves a digital trace in the environment (e.g., a state change or event log). These traces are then perceived by other agents and influence their future decisions, akin to how ants follow and modify pheromone trails in biological stigmergy.

For example, an agent that observes a recent Optimize Gas-Usage() call resulting in lower gas costs may be more likely to take that action in a similar state. These decentralized traces form a shared memory that supports adaptive, collective intelligence across the agent population, without requiring direct agent-to-agent communication.

3.4. Simulation Results

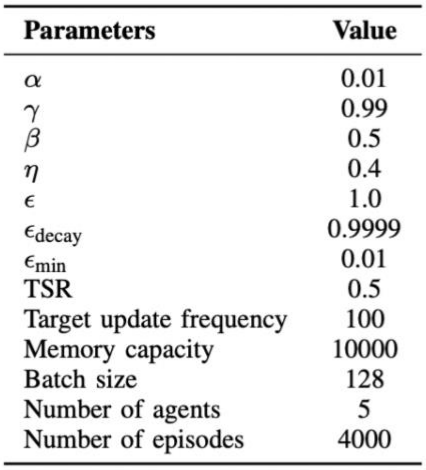
Proposed InSC algorithm represents a paradigm shift in decentralized execution by integrating RL and extended stigmergy within blockchain-based smart contracts. To evaluate its effectiveness, a Python-based simulation environment is developed, enabling rigorous testing under dynamic, multi-agent conditions. The simulation implements key features of deep Q-learning and extended stigmergic coordination, allowing agents to adaptively optimize decision-making and resource allocation within a blockchain-inspired ecosystem. This section presents the design, implementation, and evaluation of the InSC algorithm in Python 3.10, detailing the key modules, learning strategies, and comparative performance analysis against conventional smart contract mechanisms.

The simulation is implemented using the following libraries:

- NumPy & Pandas: Data processing and matrix operations
- PyTorch: Deep Q-network training
- Gym: Custom environment creation
- Web3.py: Smart contract interaction with Ethereum (off-chain integration)

Table 3.2 presents the parameters used in this simulation.

TABLE 3.2: Parameter values used in the simulation



Parameters	Value
α	0.01
γ	0.99
β	0.5
η	0.4
ϵ	1.0
ϵ_{decay}	0.9999
ϵ_{min}	0.01
TSR	0.5
Target update frequency	100
Memory capacity	10000
Batch size	128
Number of agents	5
Number of episodes	4000

The cumulative rewards per episode aggregate the rewards from agents, measuring their collaborative success in the environment. Figure 3.3 compares the evolution of cumulative rewards and average Q-values over the episodes where cumulative rewards increase significantly during the initial episodes and then plateau around episode 4000. This behavior indicates that the agent is rapidly improving its performance and successfully accumulating rewards as it learns optimal policies. The Q-values steadily increase over time, even after the cumulative rewards have plateaued. shows that while the agent's performance is consistent, it continues refining its action-value estimates, demonstrating the agent's capacity for long-term learning and policy improvement.

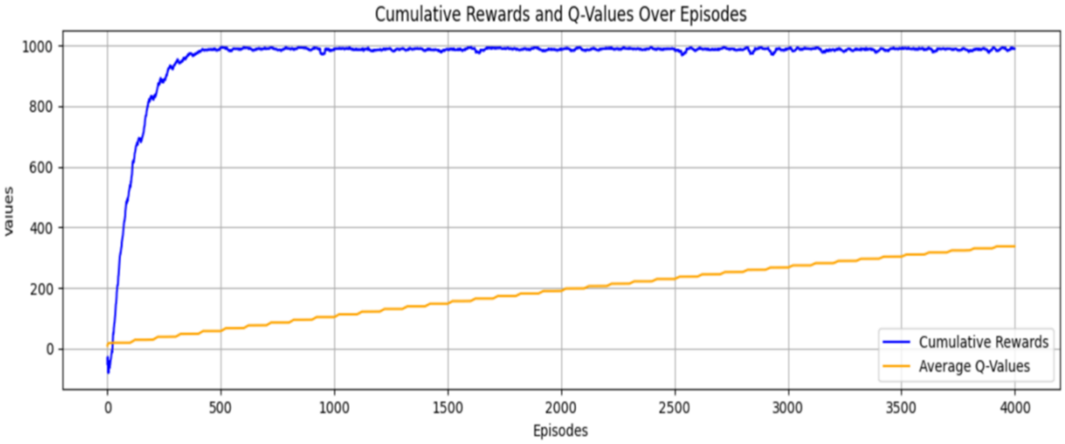


Figure 3.3: Cumulative rewards and average Q-values over the episodes

Also, Figure 3.4 illustrates the action distribution among five agents over the course of multiple episodes within a simulated smart contract execution scenario. The actions correspond to four key smart contract tasks: validation, gas optimization, execution, and auditing. The figure reveals that agents exhibit varying preferences in their action selections, indicating emergent specialization or differentiated roles. For instance, Agent 3 strongly favors execution (Action 2), while Agent 4 leans toward auditing (Action 3). This diversity suggests that agents are not acting randomly but are adapting and learning roles based on their interactions with the environment and each other, a hallmark of stigmergic coordination.

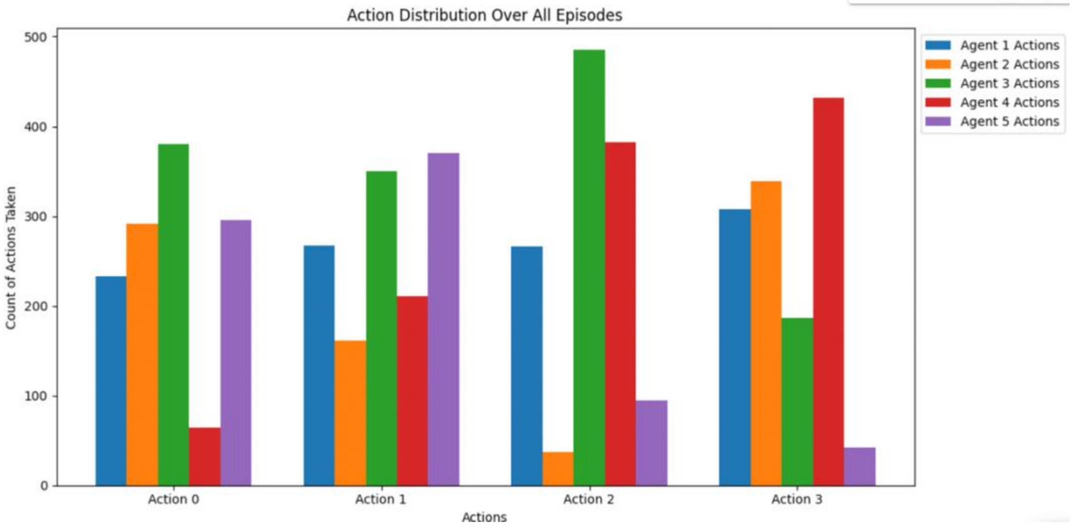


Figure 3.4: Actions distribution

Compared to a baseline such as random action selection or independent single-agent Q-learning, the multi-agent stigmergic setup demonstrates more efficient task allocation and role differentiation. This emergent behavior is critical in large-scale, decentralized systems, where centralized coordination is impractical. The results show that InSC, powered by stigmergy and reinforcement learning, can dynamically adapt to environmental demands, leading to more efficient and robust system behavior in dynamic environments.

Chapter 4

HAIB-Metaverse Architecture: Advancing Towards the Architecture of Intelligent Extended Stigmergic Agents

In this section, we propose the HAIB-Metaverse architecture, which aims to provide CI within a dynamic-aware hybrid offline-and-online media environment. Additionally, we introduce the next generation of smart contracts, which serve as the cognitive core of the HAIB-Metaverse architecture, leveraging RL and extended stigmergy. These contracts enable dynamic digital interactions, allowing intelligent agents to engage with both their environment and human users in more sophisticated ways, ensuring that decisions are informed by CI. Furthermore, we present the Metaversal Intelligence Framework, a human-AI interaction model that facilitates advanced, adaptive, and self-aware behaviors. This section is organized as follows: (1) development of the HAIB-Metaverse architecture, (2) design of intelligent smart contracts, and (3) implementation of the Metaversal Intelligence Framework.

4.1. HAIB-Metaverse Architecture

In the progression from AIB-Metaverse [12], we propose the HAIB-Metaverse architecture to ensure a more intelligent, seamless, and secure Metaverse environment. Unlike the AIB-Metaverse architecture, which primarily relies on AI, HAIB represents a significant advancement by integrating HI with AI to achieve enhanced decision-making capabilities. Within the framework of extended stigmergy, the layers of HAIB function as dynamic interfaces where human users leave and read traces in the environment, while software agents, such as intelligent smart contracts and extended stigmergic agents, autonomously act on these traces and modify them in response to changing conditions. This ongoing interaction between human inputs and autonomous agent actions allows for continuous evolution in the dynamic online environment. Figure 4.1 illustrates the multi-layered HAIB-Metaverse architecture, which integrates key components necessary for human-AI interaction within the Metaverse. The figure highlights the roles of RL agents, extended stigmergic agents, and HI in enabling CI. The new layers introduced in the HAIB-Metaverse architecture, the interaction layer, human-in-the-loop AI interactive layer, and smart decision layer as follows.

- **Interaction Layer:** This layer facilitates indirect communication between agents while collecting data from both users and the environment. Through extended stigmergic interactions, agents leave digital traces that enable other agents to sense, react, and autonomously execute actions in response to dynamic environmental changes without direct communication. Serving as a foundational layer, it transmits this information upward, thereby supporting the functionality of extended stigmergy.

- **Human-in-the-Loop/AI Interactive Layer:** This layer is central to the HAIB-Metaverse architecture, integrating HI with agent activities by processing data from the interaction layer. It analyzes digital traces and environmental data, allowing users to influence the system in real time. By combining human input with the actions of intelligent agents, the system dynamically adapts to user needs and environmental changes. Human feedback adjusts agent strategies, facilitating real-time, adaptive interactions. RL agents in smart decision layer, leverage data to optimize their actions effectively. The decision-making process is inherently multi-layered, influenced by the agents' prior experiences, real-time environmental inputs, and extended stigmergic feedback collected within this layer. This integration allows RL agents to learn from both past interactions and ongoing dynamics, continually refining their strategies to enhance performance in complex and variable contexts. Also, superposition enables agents to simultaneously consider multiple actions, allowing them to evaluate potential outcomes before making decisions. This enhances flexibility and adaptability. Meanwhile, decay helps agents transition from exploring new possibilities to exploiting known optimal actions, improving decision-making efficiency over time. Diffusion promotes the sharing of knowledge and experiences among agents through interactions, facilitating the spread of effective strategies and fostering collective intelligence and collaboration.

- **Smart Decision Layer:** This layer is the decision-making core, driven by InSCs (discussed in the next subsection) that manage and optimize multi-agent interactions. It processes comprehensive data from both the interaction layer and the human-in-the-loop AI interactive layer to break down complex objectives into manageable tasks. The InSCs facilitate cooperation among agents, ensuring efficient resource allocation and task execution. By drawing on human feedback and agent interactions, this layer ensures that decisions are aligned with system-wide goals and dynamically adjusted based on the current context, reinforcing the principles of CI. This layer serves as the system’s cognitive engine, continuously refining strategies to achieve optimal outcomes.

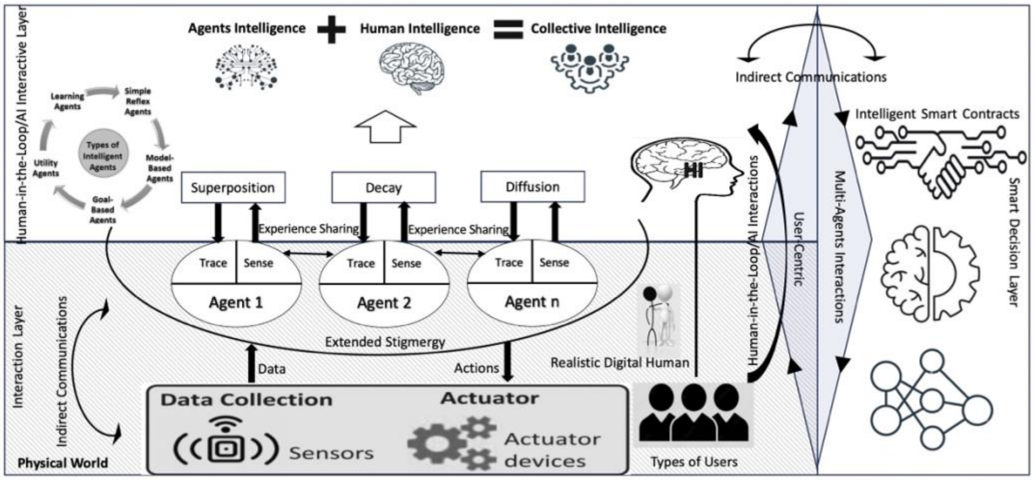


Figure 4.1: New three layers of the HAIB-Metaverse architecture

In contrast to traditional smart contracts, which provide secure and deterministic execution but lack adaptability and self-awareness in dynamic environments like the Metaverse, the HAIB architecture introduces a solution to these limitations. By integrating extended stigmergic agents and RL, the HAIB framework enhances the adaptability and intelligence of smart contracts in decentralized systems. Similar to the SEB and SIRL frameworks, which enable adaptive coordination and collaboration within blockchain environments, HAIB combines extended stigmergy-driven communication with RL to create more intelligent, flexible, and responsive smart contracts that can evolve in dynamic environments. Extended stigmergic agents facilitate decentralized coordination by interacting with and modifying their environment, influencing the behavior of other agents. This interaction fosters greater efficiency and adaptability in the system, leveraging cumulative rewards based on metrics such as gas optimization, action efficiency, and human-system interaction.

Additionally, extended stigmergy-inspired updates allow agents to exchange indirect information, enhancing collective decision-making in complex, dynamic settings. In contrast, AIB architectures primarily use RL to improve immersive experiences, such as adaptive Metaverse video delivery. In these systems, models like A3C optimize Quality of Experience (QoE) through efficient resource allocation and network adaptation, focusing on user-facing outcomes. While AIB emphasizes immersive virtual experiences via supervised system feedback, HAIB uniquely combines RL with extended stigmergy to align system actions with human goals in real time. This dual-focus on human-AI collaboration and autonomous adaptability positions HAIB as an innovative architecture, advancing decentralized intelligence and smart contract systems.

4.2. On/Off-Chain Methodology

In Ethereum, smart contracts are stored and executed on Contract Accounts (CAs), traditionally passive entities that rely on activation by transactions from either External Owned Accounts (EOAs) or other CAs. This on-chain setup, where each function execution is verified by all network miners, ensures deterministic and trustworthy outputs. However, substantial gas costs and potential privacy issues arise when computationally intensive or sensitive tasks are executed on-chain. To address these challenges, a dual layer on/off-chain execution approach has emerged, allowing contracts to operate more actively and adaptively. In this hybrid setup, only essential, public, and low-cost functions remain on-chain to handle core contract logic, while complex, privacy-sensitive operations are processed off-chain. This enables the off-chain environment to handle intensive computations, actively monitor real-time conditions, and send only essential updates to the on-chain contract. The result is a system optimized for resource efficiency, capable of executing actions based on current data while reducing gas costs, preserving privacy, and alleviating network congestion. Integrating on-chain and off-chain components has thus proven effective for balancing security, performance, and resource optimization [58][59].

In our implementation, we adopt this hybrid paradigm by partitioning responsibilities between two layers:

On-Chain Layer: This includes immutable smart contract functions such as validating and logging events. These operations are critical to the integrity of the decentralized system and are publicly verifiable, ensuring tamper-resistance and auditability. Only minimal and deterministic logic is maintained here to minimize gas usage.

Off-Chain Layer: High-complexity processes, including RL decision-making, extended stigmergic trace evaluation, gas optimization strategies, and multi-agent coordination, are executed externally using Python-based simulations and machine learning libraries like PyTorch. For example, the TSR metric is computed off-chain during the RL agent's training phase. While blockchain constraints limit direct computation of complexity-weighted metrics on-chain due to gas and storage limitations, off-chain agents can log transaction outcomes, retrieve gas usage, and apply pre-defined complexity weights to calculate TSR in real-time. This hybrid design maintains blockchain integrity while enabling adaptive agent learning. The off-chain agents interact with the blockchain via APIs using Infura, MetaMask, and send actionable decisions back to the on-chain contract through signed transactions.

To support adaptive data access and decision logic, we integrate an Oracle-based relational database. This database stores dynamic environmental states, interaction logs, reward histories, and stigmergic feedback traces. By handling this data off-chain, the system achieves both rapid retrieval and the scalability needed for real-time decision support, without bloating the blockchain.

This hybrid design allows intelligent agents to:

- Evaluate and learn from collective agent behavior through updated Q-values and stigmergic signals.
- Optimize actions dynamically in response to environmental or contract state changes.
- Minimize the frequency and cost of on-chain interactions while ensuring that key contract invariants are preserved.

This architecture achieves a secure, gas-efficient, and intelligent contract execution model, well-suited for dynamic, multi-agent ecosystems like those envisioned in the Metaverse.

4.3. Metaversal Intelligence framework: A Human-AI Interaction Model

Human-AI interaction models are foundational frameworks that enable efficient interactions within virtual environments. As discussed in [3], shifting to human-centric services, rather than data-centric ones, will significantly enhance user experiences in the Metaverse. In this context, the role of extended stigmergy in intelligent systems, as explored in [60], is crucial. Extended stigmergy facilitates indirect coordination and communication through environmental traces, a process that is vital for both natural and artificial cognitive systems. For example, in natural systems, such as insect colonies, stigmergy allows for collective behavior and decision-making, where individual actions are guided by environmental cues left by others. In artificial systems, such as swarm robotics, stigmergy enables robots to perform complex tasks through simple, decentralized interactions. This concept also applies to neural processes in the brain, where neurotransmitters and neuromodulators act as stigmergic agents, influencing neural activities and supporting cognitive functions. Thus, stigmergy serves as a unifying principle across different scales of intelligent systems, linking individual behaviors to collective outcomes through environmental interactions. Furthermore, as discussed in [61], integrating smart contracts with AI can serve as an effective governance tool within a blockchain-driven Metaverse.

Our proposed Metaversal Intelligence framework aims to develop a robust human-AI interaction model that integrates AI, extended stigmergy mechanism, and blockchain technologies to enhance user experiences within the Metaverse. As mentioned before, the system incorporates various intelligent schemes to implement CI where RL agents are trained to iteratively learn optimal strategies through continuous interaction with the environment, adapting to real-time changes and improving decision-making capabilities. InSCs combine RL with traditional contract mechanism to create adaptive, rule-based interactions that dynamically adjust based on agent behavior and environmental conditions, while extended stigmergy agents enable indirect communication among agents through digital pheromones, promoting effective coordination in MAS.

On the other hand, human intelligence is integrated through a cognitive nexus intelligence framework, ensuring alignment with human values and facilitating interactive learning and collaboration between users and AI agents. This comprehensive approach enhances the adaptability and responsiveness of intelligent systems within the Metaverse, providing a secure, efficient, and user-centric interaction environment. The system offers a promising approach for creating environments where human participants and entities in DAOs using blockchain technologies can collaborate more effectively.

4.4. Simulation Result

In this section, I link the proposed InSC algorithm within the blockchain environment using a dual-layer approach: an on-chain layer for decentralized execution in Solidity and an off-chain layer in Python for computational efficiency and real-time adaptation of agent strategies. This setup allows for a comparative analysis of conventional stigmergy and extended stigmergy frameworks, focusing on gas usage efficiency and cumulative reward performance. The simulations leverage a hybrid architecture that combines on- chain and off-chain computations, with Solidity facilitating essential blockchain interactions and Python implementing RL and stigmergy algorithms. The Solidity-based smart contracts were coded, tested, and deployed on the Sepolia Testnet via Remix IDE, ensuring that critical operations and immutable data remain secure and tamper-proof. This blockchain environment offers a stable testing platform.

Complementing the on-chain contract, the Python off-chain component enables advanced computations, particularly RL and extended stigmergy mechanisms, which would be gas-intensive if run directly on-chain. By managing these calculations off-chain, our approach reduces gas expenditure and supports high-speed processing, enhancing adaptive agent interactions and overall system performance. MetaMask serves as the wallet solution, enabling secure transaction signing, while Infura connects the Python environment to the Ethereum network on Sepolia, allowing a realistic and cost-effective test environment. Python handles multi-agent simulations and RL updates, which are subsequently communicated to the on- chain contract to update states and process rewards. This setup achieves a seamless balance between performance (transaction throughput and latency) and security, with each environment maximizing its unique strengths.

4.4.1 Performance Comparison: Conventional vs. Extended Stigmergy

The results of the simulations were analyzed over 100 episodes, evaluating both conventional and extended stigmergy strategies based on cumulative rewards and gas usage in the Ethereum environment. Extended stigmergy consistently demonstrated lower gas usage compared to conventional stigmergy, as seen in Figure 4.2. By offloading the RL and stigmergy calculations to the off-chain layer, agents operating under extended stigmergy achieved optimized resource allocation. This efficiency is due to the dynamic updates facilitated by extended stigmergy, which allows agents to adjust their behavior based on evolving contract states and collective feedback.

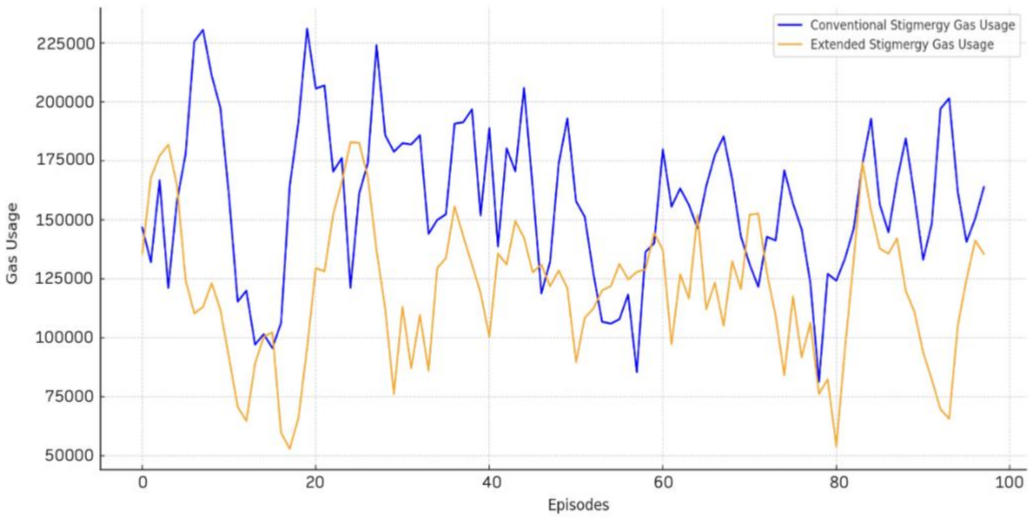


Figure 4.2: Gas Usage Comparison Between Conventional and Extended Stigmergy

The cumulative rewards per episode reflect the aggregated success of agents, capturing their collaborative performance within the environment. As illustrated in Figure 4.3, agents utilizing extended stigmergy achieved significantly higher cumulative rewards compared to those employing conventional stigmergy. This improvement is attributed to extended stigmergy agents' ability to rapidly adapt their strategies in response to environmental changes and interactions with other agents. By incorporating both individual and collective experiences into the extended stigmergy update process, these agents effectively optimize their strategies over time, leading to maximized long- term rewards.

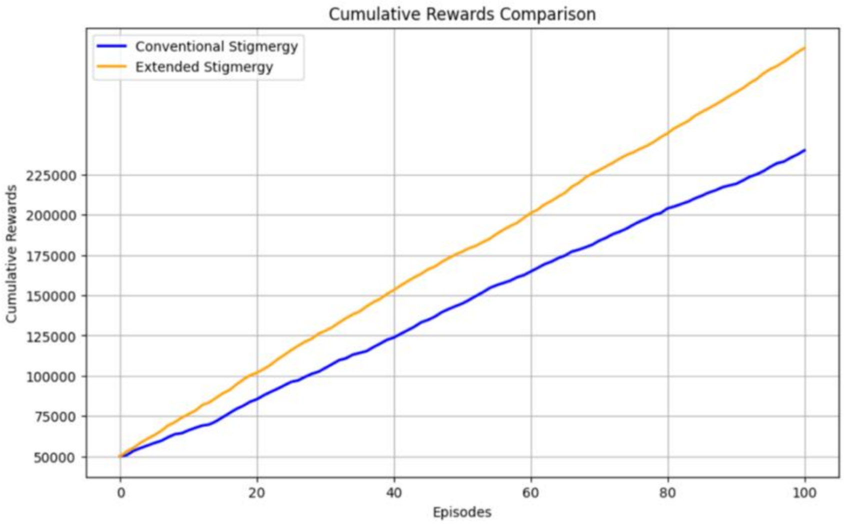


Figure 4.3: Cumulative Rewards Comparison Between Conventional and Extended Stigmergy

This hybrid approach combining on-chain and off-chain strategies allows for an efficient simulation of intelligent contracts, where agents can learn and adapt while keeping blockchain interactions cost-effective. The results demonstrate that extended stigmergy not only enhances gas efficiency but also significantly improves agent performance within the dynamic smart contract environment.

To validate the effectiveness of the proposed InSC framework, we compare it against conventional stigmergy-based smart contracts. Table 4.1 highlights key differences in adaptability, decision-making efficiency, and blockchain cost optimization.

Table 4.1: Comparative analysis of smart contracts: conventional vs. extended stigmergy

Feature	Conventional Stigmergy	Extended Stigmergy (InSC)
Adaptability	Moderate Adaptability	High Adaptability with Dynamic Real-Time Updates Based on Agent Feedback
Decision Efficiency	Limited To Pre-Set Heuristics	RL-Enhanced Adaptive Decision-Making
Gas Optimization	Higher Gas Consumption	Reduced Gas Usage Via Off-Chain Rl Updates
Multi-Agent Interaction	Limited Coordination	Enhanced Collaboration Through Extended Stigmergy Mechanisms
Reward Optimization	Static Reward Structure	Adaptive Reward Accumulation Via Q-Learning

By integrating off-chain RL and extended stigmergic mechanisms, the proposed approach enables:

1. **Secure and Efficient Execution:** Maintains blockchain security while optimizing computations through off-chain processing.
2. **Reduced Gas Costs:** Lowers transaction expenses by offloading RL and stigmergy updates off-chain.
3. **Scalability:** Enhances multi-agent coordination for improved system scalability.
4. **Intelligent Adaptability:** Enables real-time decision-making using RL and collective intelligence.

This hybrid model demonstrates the potential of extended stigmergy to drive the next generation of intelligent smart contracts by optimizing both performance and cost-efficiency.

4.4.2 Comparison of Gas Optimization Methods

As mentioned before, optimizing gas consumption in Ethereum smart contracts is essential for enhancing scalability and cost efficiency. Several approaches have been developed to minimize gas usage, including off-chain execution strategies, manual Solidity optimizations, and learning-based adaptive frameworks. In this section, we compare the proposed InSC framework with two notable gas optimization studies: Lazy contracts [62]and smart contracts refinement [63].

1. Lazy Contracts: Off-chain Execution for Reduced Gas Costs

Lazy Contracts implement an off-chain execution model, where only dispute resolution occurs on-chain, leading to a 55.4% reduction in gas usage. The core idea is that contract states and execution results are agreed upon off-chain, and only in cases of disagreement is an on-chain execution triggered, penalizing dishonest participants. While highly efficient in reducing gas fees, this method introduces a reliance on off-chain trust assumptions, which may not be ideal for fully decentralized applications requiring immutable execution [62].

2. Smart Contracts Refinement for Gas Optimization

This approach focuses on refining smart contract code structures, particularly loop control mechanisms, to enhance gas efficiency. An empirical study involving 72 Solidity smart contracts demonstrated an average gas cost reduction of approximately 21%. Although this technique requires manual code analysis and restructuring, it offers substantial gas savings without altering the execution model or introducing additional trust assumptions [63].

3. Proposed InSC Framework

The proposed InSC framework introduces a learning-based optimization approach, where multi-agent RL and extended stigmergy enable adaptive gas optimization. By leveraging off-chain computations for learning and decision-making, InSC reduces on-chain processing overhead, leading to a 32–33% reduction in gas usage. Unlike Lazy contracts, which rely on off-chain mutual agreement, InSC operates fully on-chain while benefiting from off-chain learning to optimize decision-making dynamically.

Table 4.2 provides a comparison of these methods based on gas optimization efficiency, adaptability, execution model, and trust assumptions.

Table 4.2: Comparative analysis: lazy contracts and smart contracts refinement vs. InSC

Method	**Gas Reduction(%)**	**Execution Model**	**Adaptability**	**Trust Assumptions**
Lazy Contracts [61]	55.4%	Most Off-Chain Execution	Moderate (Trigger-Based)	Requires Off-Chain Consensus
Smart Contracts Refinement [62]	21%	On-Chain Execution	Low (Code-Level Only)	No Trust Required
InSC (Proposed Method) [64]	32–33%	Hybrid (On-Chain and Off-Chain)	High (Dynamic, Real-Time Updates)	No Trust Required

The proposed InSC framework strikes a balance between efficiency, adaptability, and decentralization, offering competitive gas optimization (32–33%) while maintaining trust less execution. It dynamically learns and optimizes contract execution, providing continuous improvements, unlike smart contracts refinement, which rely on static enhancements. InSC ensures trust less execution and benefits from adaptive optimization, making it ideal for decentralized systems. While Lazy contracts achieve the highest gas savings, they rely on off-chain execution, which makes them less suitable for trust less decentralized systems. In contrast to Lazy contracts, which require off-chain agreements, InSC maintains complete trust and decentralization by integrating both on-chain and off-chain processes.

Chapter 5

Conclusions and Future Work

5.1. Conclusions

This study has presented a novel approach to enhancing decentralized intelligence by integrating the HAIB-Metaverse architecture and the InSC framework. The proposed framework leverages RL and extended stigmergy to create a user-centric, adaptive, and self-executing smart contract system capable of optimizing multi-agent interactions. By establishing a seamless interface between human intelligence and artificial intelligence, the HAIB-Metaverse architecture fosters dynamic decision-making, efficient resource allocation, and autonomous collaboration. These innovations address key challenges in decentralized environments, such as adaptability, scalability, and computational efficiency, marking a significant advancement over conventional smart contract mechanisms.

A key contribution of this work is the introduction of extended stigmergy as a mechanism to enhance multi-agent coordination and environmental adaptability within the Metaverse. Unlike conventional stigmergy, which relies on static traces, extended stigmergy dynamically modulates interactions based on real-time environmental feedback, allowing smart contracts to evolve and respond intelligently to changes. Experimental evaluations demonstrate that the proposed framework reduces gas consumption by 32–33% while increasing cumulative rewards. By allowing agents to autonomously learn, adapt, and self-organize, the framework provides an intelligent alternative to traditional blockchain-based contracts, which often suffer from rigid execution constraints and inefficiencies.

Furthermore, the integration of a human-in-the-loop paradigm within the HAIB-Metaverse enables a more interactive and responsive decentralized ecosystem, where smart contracts can incorporate both algorithmic intelligence and human expertise. This hybrid approach ensures that smart contracts are not only autonomous and self-executing but also capable of aligning with evolving user preferences and external conditions. By bridging human cognition, AI, and blockchain automation, this work paves the way for a new generation of intelligent, self-optimizing, and highly adaptable smart contracts.

The significance of this research extends beyond theoretical advancements, offering practical implications for real-world blockchain applications. The HAIB-Metaverse architecture provides a scalable foundation for decentralized finance (DeFi), supply chain management, digital governance, and other multi-agent coordination systems where intelligent, adaptive smart contracts can enhance operational efficiency and decision-making autonomy. The experimental validation confirms that the proposed framework effectively overcomes the static limitations of traditional smart contracts, enabling more fluid, efficient, and intelligent interactions in blockchain-driven environments.

5.2. Future Works

While this study has demonstrated the effectiveness of integrating RL and extended stigmergy in intelligent smart contracts within the HAIB-Metaverse architecture, several avenues remain open for further research. Future work can focus on enhancing adaptability and economic incentives within decentralized environments by extending the current framework in the following directions:

1. Advanced Token Engineering for Intelligent Smart Contracts

A well-designed token economy is essential for aligning incentives, optimizing resource allocation, and enhancing agent cooperation in decentralized environments. Future work could focus on:

- Dynamic Tokenized Reward Mechanisms: Designing adaptive incentive structures where token rewards are dynamically adjusted based on agent contributions, contract performance, and network conditions.
- Energy-Efficient Token Economics: Exploring eco-friendly tokenomics models that integrate proof-of-useful-work (PoUW) or proof-of-collaboration (PoC) to incentivize efficient execution of intelligent smart contracts while minimizing energy consumption and blockchain congestion.

2. AI-Driven Legal Compliance for Smart Contracts

Developing regulation aware InSCs that dynamically adapt to legal frameworks while maintaining decentralized execution and automation.

By exploring these research directions, future advancements in stigmergy-driven smart contracts, token engineering, and decentralized intelligence will contribute to the next generation of adaptive, scalable, and user-centric blockchain ecosystems. These enhancements will strengthen the role of intelligent smart contracts in shaping decentralized economies, governance models, and human-AI collaboration in the Metaverse and beyond.

Chapter 6

Publications

Below is a list of publications at INRS. Following this, I provide a summary of each:

1. M. Soltanshahi, M. Maier, "Metaversal Intelligence: Unifying Human-AI Interactions in Human-in-The-Loop AIB-Metaverse", Elsevier, computer networks journal, Volume 269, , pp. 111425,ISSN 1389-1286, 2025.
2. M. Soltanshahi, N. Hosseini, and M. Maier, chapter title: “Toward Future Metasystems: From Today’s CPS to Tomorrow’s Cyber-Physical-Social Systems (CPSS) in the Emerging Metaverse” in “Cyber Physical System 2.0: Communication and Computational Technologies”, (Editors: Amitkumar V. Jha and Bhargav Appasani), CRC Press Publisher, ISBN: 978-104025220-8;978-103261463-2, 2024.
3. M. Maier, M. Soltanshahi, and N. Hosseini, "Metaverse as the New Eleusis 2.0: Are We in the Midst of the Next Renaissance?", IFSA Publishing, Blockchain and Cryptocurrency, vol. 1, no. 1, pp. 1-17, Sept. 2023.
4. M. Maier, N. Hosseini, and M. Soltanshahi, "INTERBEING: On the Symbiosis between INTERnet and Human BEING", IEEE Consumer Electronics Magazine, Special Issue on Metaverse and eXtended uniVerse (XV): Opportunities and Challenges for Consumer Technologies, vol. 13, no. 3, pp. 98-106, May 2024.

1. Metaversal Intelligence: Unifying Human-AI Interactions in Human-in-the-Loop AIB-Metaverse

This publication presents the HAIB-Metaverse architecture, a novel architecture that integrates RL, extended stigmergy, and blockchain technology to achieve CI, enable InSCs, and optimize multi-agent interactions. Unlike traditional smart contracts that execute predefined rules, the proposed InSCs adapt dynamically, learning from extended stigmergic digital traces to improve efficiency and decision-making. By incorporating human-in-the-loop layer, the HAIB-Metaverse architecture establishes an interactive AI-driven ecosystem where human agents collaborate with decentralized AI entities, refining contract execution, resource allocation, and transaction optimization. Experimental evaluations validate the effectiveness of this approach, demonstrating a 32–33% reduction in gas consumption and improved multi-agent learning efficiency in blockchain simulations.

A significant contribution of this research is the integration of DQL with extended stigmergy, enabling smart contracts to continuously adapt based on real-time blockchain interactions. Unlike conventional blockchain execution models, which are rigid and computationally expensive, InSCs refine execution strategies autonomously. This adaptability is further enhanced through a hybrid on-chain/off-chain computation strategy, which balances security, efficiency, and cost reduction. By dynamically selecting the most cost-effective execution path, this model ensures high computational efficiency while maintaining blockchain security guarantees.

Additionally, this study introduces a multi-layer interaction model, combining extended stigmergic agents, AI-driven contract intelligence, and decentralized governance mechanisms to create a scalable and self-regulating Metaverse infrastructure. This model addresses critical challenges in gas optimization, decentralized contract intelligence, and adaptive AI-driven governance, providing a foundation for the next-generation Web3 economy. The HAIB-Metaverse redefines human-AI collaboration in blockchain ecosystems, enabling self-organizing intelligent environments that evolve through continuous learning and adaptive optimization, setting the stage for autonomous economic systems in the Metaverse.

2. Toward Future Metasystems: From Today's CPS to Tomorrow's Cyber-Physical-Social Systems (CPSS)

This publication explores the evolution from Cyber-Physical Systems (CPS) to CPSS, emphasizing how human, computational, and physical systems can be seamlessly integrated within the emerging Metaverse. This study takes a system-level perspective, addressing how technological infrastructures must adapt to incorporate social intelligence, decentralized decision-making, and self-organizing networks. It underscores the need for an interactive, AI-driven Metaverse, where stigmergic intelligence enables dynamic coordination between human and machine agents.

A key focus of this research is defining the fundamental shift from CPS to CPSS, where autonomous agents operate beyond rigid cyber-physical interactions to engage in socially aware, adaptive, and scalable digital ecosystems. By leveraging stigmergy-enhanced intelligence, CPSS frameworks facilitate emergent collective behaviors, allowing decentralized systems to evolve in response to human intent, environmental stimuli, and economic incentives. This transition introduces new opportunities for governance, coordination, and efficiency in large-scale Metaverse infrastructures, ensuring they remain resilient, adaptive, and human-centric.

Furthermore, this study examines challenges in CPSS governance and interaction models, addressing how autonomous decision-making processes can be balanced with social accountability, transparency, and ethical considerations. The integration of stigmergic mechanisms and AI-driven infrastructures provides a pathway for scalable, decentralized coordination, paving the way for self-regulating Metaverse environments that align with human and societal needs. This research paves the way for next-generation techno-social systems, highlighting their potential to transform human-computer interaction, enhance collaborative intelligence, and redefine decentralized governance in the digital era.

3. Metaverse as the New Eleusis 2.0: Are We in the Midst of the Next Renaissance?

This paper explores how blockchain, stigmergy, and tokenization can enhance CI and human-AI collaboration in the context of 6G, the Metaverse, and Society 5.0. It argues that future networks should go beyond merely connecting devices and instead enable a stigmergy-enhanced techno-social system, where human and AI interactions are self-organized through decentralized incentives. By leveraging blockchain as connective tissue, human actions can leave stigmergic traces (digital pheromone trails) that guide decision-making, similar to how ants coordinate through pheromones. This approach transforms traditional communication networks into adaptive, intelligent ecosystems, where blockchain-based tokenized digital twins record and optimize collective behaviors, steering society toward higher levels of intelligence.

A key contribution of this paper is its multilayer token engineering DAO framework, which incentivizes purposeful human-AI interactions using blockchain-based programmable incentives. The study also explores the impact of gamification and play-to-earn models, demonstrating how integrating blockchain into online and offline games enhances economic and social interactions in the Metaverse. By doing so, the paper frames the Metaverse as "Eleusis 2.0", a transformative space akin to the ancient Eleusinian Mysteries, where immersive experiences unlock new cognitive and economic potentials. The proposed system envisions a shift from Industry 4.0’s commercial focus to Society 5.0’s human-centered intelligence, ensuring that decentralized technologies serve social and economic well-being.

4. INTERBEING: On the Symbiosis between INTERnet and Human BEING

This publication introduces INTERBEING, a framework that examines the symbiotic evolution of the Internet and human cognition within the Metaverse and the eXtended meta-uni-omni-Verse (XV). It explores how AI-driven digital ecosystems, tokenized digital twins, and stigmergy principles enable self-organizing, intelligent environments. Unlike previous studies that focus on smart contracts, decentralized decision-making, or system architectures, this work presents a biologically inspired digital society, where hyperintelligent life-like digital organisms symbiomimic biological superorganisms to create stigmergic virtual societies. By integrating AI, decentralized computing, and blockchain, the study envisions a dynamic, real-time adaptive environment that strengthens the connection between human intelligence and digital networks in future 3D spatial Internets.

A core aspect of this research is the expansion of the reality-virtuality continuum into a third, sociality dimension, where collaborative XR experiences foster collective intelligence in decentralized environments. By leveraging stigmergic reinforcement learning mechanisms, intelligent agents leave programmable digital traces, influencing human-machine interactions in Web3-based digital societies. The study also introduces cybernetic organisms, bridging AI, blockchain, and the biological evolution of intelligence, leading to self-regulating, scalable AI-driven interactions within the 6G-enabled Metaverse. Furthermore, tokenized digital twins play a crucial role in enhancing autonomous decision-making and decentralized governance, ensuring seamless interoperability across mixed-reality environments.

This publication contributes to next-generation AI-governed digital ecosystems, addressing key challenges in sensor integration, interoperability, and governance in cross-reality environments. By mapping the biological structure of fungal networks to cybernetic AI, the study introduces new models of information exchange and resource optimization. These findings offer a pathway to a future where human-AI collaboration transcends traditional interfaces, establishing a fully immersive, intelligent, and stigmergy-enhanced Metaverse that integrates biological and digital intelligence in a self-organizing, decentralized framework.

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