

The Evolution of Autonomous AI Platforms Integrating LLM Inference, Multi-Agent Reinforcement Learning, and Self-Healing Architectures

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Abstract—Enabling adaptive decision-making, learning, and autonomous behavior of modern intelligent systems with minimal human intervention. Recent developments in Large Language Models (LLMs), Multi-Agent Reinforcement Learning (MARL), and self-healing architectures have greatly improved the capabilities of autonomous systems in complex and distributed environments. The survey will review the history of autonomous AI systems and discuss the use of LLMs as cognitive engines for reasoning, planning, and natural language dialogue. Also, it covers the methods of MARL and how they allow multiple intelligent agents to cooperate and compete. Moreover, self-healing architectures studied, showing their contribution to improving resilience of the systems via fault tolerance, automation of restoration, and prediction-based maintenance. Different deployment models, architectural approaches, applications, and performance measures will be considered to give a complete picture of contemporary autonomous AI systems. Additionally, important problems such as scalability, reliability, security, privacy, explain ability, and resource limitations will be discussed. Emerging trends of agentic AI systems, autonomous AI operating systems, foundational models for MARL, and architectures inspired by AGI will also be presented. This survey will present information about the convergence of LLMs, MARL, and self-healing approaches and possible future research directions in the field of autonomous AI systems.

Keywords—Autonomous Artificial Intelligence (AI), Large Language Models (LLMs), Multi-Agent Reinforcement Learning (MARL), Agentic AI, Self-Healing Systems, Autonomous Agents, Edge-Cloud Computing.

I. INTRODUCTION

The fast advancement of artificial intelligence technology has revolutionized the operating environment of today's businesses, from automation to full autonomy, where the system decisions making and acts on its own accord. Autonomous AI technology is indeed a revolutionary concept in the way business organizations conduct their operational

and financial processes [1][2]. An autonomous AI involves the use of technologies such as machine learning, reinforcement learning, LLMs, and intelligent agents to complete intricate operations within an environment that is not constant and stable [3]. Autonomous AI continually perceives the environment around them, analyzes data, makes decisions, and acts upon them in order to accomplish certain goals. Moreover, these types of platforms may also include self-healing or self-learning abilities to make them more efficient [4][5].

Large Language Models (LLMs) refer to sophisticated AI models that have been created to comprehend, generate, and analyze human languages. The models developed by employing deep learning methods with Transformer architecture and are trained on vast amounts of textual data obtained from different sources, like books, websites, research papers, and other digital repositories [6]. The training process involves learning the patterns, structures, meanings, and contextual relationships in the languages, thereby allowing LLMs to perform various language processing activities like text generation, question-answering, summarizing, translating, and reasoning. The development of LLMs has marked a paradigm shift in the domain of artificial intelligence because it is only through LLMs that machines can interact in an intelligent manner with humans. Unlike earlier NLP technologies, which depended on manually engineered models, LLMs can generalize across several domains without needing task-specific learning [7]. Their inference capabilities further enable autonomous agents to perform reasoning, planning, and adaptive decision-making in dynamic environments.

A sophisticated subfield of Reinforcement Learning (RL) that is concerned with the analysis of the interactions, learning process, and decision-making involving multiple intelligent agents at once is Multi-Agent Reinforcement Learning (MARL) [8]. Multi-agent reinforcement learning considers several smart agents that may be collaborating, battling, or

both while attempting to accomplish specific goals, compared to traditional learning, where a single intelligent agent learns by interacting with its surroundings [9]. The multi-agent reinforcement learning technique introduces multi-agent frameworks and leverages the concepts of reinforcement learning to enable decentralized choice-making. With this technique, agents learn their optimal policy through trial-and-error interaction with their surroundings and with other intelligent agents.

Artificial intelligence computing systems capable of automatically recognizing, diagnosing, and repairing any failure with little to no human intervention are self-healing architectures. By drawing inspiration from biological self-repairing processes, self-healing computing systems constantly scan their surroundings for any anomaly [10], and then take necessary steps to repair that anomaly. The key goal of implementing self-healing capabilities is to improve the overall reliability, robustness, availability, fault tolerance, and operational effectiveness of the system involved.

A. Structure of the Paper

The organization of the paper as follows: Section II presents an overview of Autonomous AI Platforms, discussing their fundamental concepts, Section III examines the role of LLMs in Autonomous Systems, Section IV explores Multi-Agent Reinforcement Learning (MARL) for Autonomous Intelligence, Section V discusses Self-Healing Architectures, Section VI provides a literature review of recent research, Section VII discussing conclusion and future work.

II. AUTONOMOUS AI PLATFORMS: FOUNDATIONS AND EVOLUTION

Smart systems that can detect their surroundings, make judgements, and act without human assistance are referred to as artificial intelligence (AI). In contrast to conventional AI, which works using predetermined instructions provided by human beings, autonomous AI has the capability of modifying its actions in accordance with changes in its environment and based on its previous learnings [11]. The main traits of an autonomous AI system include self-learning capabilities, adaptability, goal-oriented decisions, and timely reaction capabilities.

A. Evolution of Intelligent Agents

Artificial intelligence makes it possible to create smart agents that can function in place of people or machines and exhibit certain smart behaviors [12][13]. Every intelligent agent has the ability to use sensors to detect and respond to its surroundings. There are typically three main categories of intelligent agents:

- **Human agents:** The human body's many organs, like the eyes and hearing, serve as sensors, while other bodily parts, such as the hands and legs, serve as actuators.
- **Robot agents:** They use various technologies, such as motors as actuators and cameras as sensors.
- **Software agents:** Some files are used as actuators, while others use the contents of files or other packages received over a network as a sensor.

These agents are accessible and have a variety of uses in business, industries, schools, and different governmental or private organizations for particular objectives like transportation management [14], Geographic systems

oversight, traffic and incident management, etc. By integrating several functions into the same system, intelligent machines are progressively becoming entirely self-sufficient systems [15][16].

B. Levels of Autonomy in AI Systems

It can be categorized into different levels of autonomy based on the degree of human involvement required during operation. On the most fundamental level, AI works as decision support tools, which give recommendations but where humans have the full authority over their functioning. Systems at higher levels of autonomy can carry out predetermined tasks without any human intervention, be able to adjust themselves according to the environment and take decisions without much interference from humans. Increased levels of autonomy are achieved due to advancements in fields like machine learning, reinforcement learning, intelligent agents, and adaptive systems [17][18]. The responsibilities that a user (human or AI) may assume while engaging with an agent in a task-based environment are the focus of five levels of independence for AI agents as shown in Figure 1. below:

- **L1:** Operator user gives instructions and makes choices, while the agent takes action.
- **L2:** Collaborator user and agent work together to organize, assign, and carry out tasks.
- **L3:** Consultant Agents take the initiative but ask users for their preferences and areas of expertise.
- **L4:** The user only interacts with the approver agent in hazardous or predetermined situations.
- **L5:** Under user supervision, the user as an Observer Agent has complete autonomy.

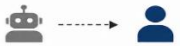
L1 Operator		User directs and makes decisions, agent acts.
L2 Collaborator		User and agent collaboratively plan, delegate, and execute.
L3 Consultant		Agent takes lead but consults user for expertise/preferences.
L4 User as an Approver		Agent engages user only in risky or prespecified scenarios.
L5 User as an Observer		Agent operates with full autonomy under user monitoring.

Fig. 1. Five levels of autonomy for AI agents

C. Core Components of Autonomous Platforms

AI systems are made up of multiple layers that work together to ensure intelligence and adaptability.

- The perception layer is responsible for acquiring information from sensors or other data feeds and external sources.
- The reasoning and inference layer works on interpreting the collected information, enabling decision-making.
- Learning takes place at the learning layer; most learning modules use machine learning and reinforcement learning methods to gradually enhance the system's performance.
- Knowledge Base and Data Management component stores and organizes information required for intelligent decision-making [19].
- Decision-Making Engine determines the most appropriate action based on available information

- Planning and Orchestration Layer translates decisions into executable plans.
- Execution and Actuation Layer carry out actions selected by the decision-making engine.
- Feedback and Monitoring System ensures the effectiveness of autonomous actions.
- Human-Agent Interaction Layer although autonomous systems minimize human involvement, users still provide oversight and governance.

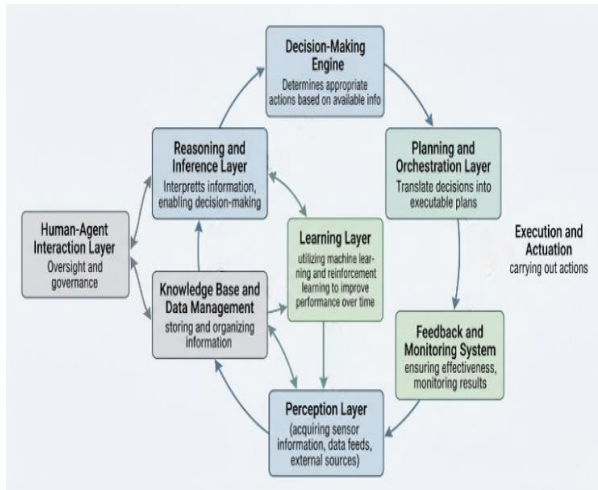


Fig. 2. Core Components of Autonomous Platform

Multi-agent coordination illustrated in Figure 2. provides a means for coordinating and communicating between multiple distributed agents to enhance scalability and problem solving [20].

III. LARGE LANGUAGE MODELS (LLMs) IN AUTONOMOUS SYSTEMS

AI-based models trained on vast data that includes texts, codes, and structured data are known as The Large Language Models (LLMs). The examples include GPT, Llama, and Gemini. The LLMs have strong skills for natural language processing, reasoning, planning, knowledge retrieval, and decision making. In the case of the autonomous system, the LLM is used as a cognitive system that allows intelligent interaction, reasoning, planning, and decision making. The autonomous system based on LLMs differs from the traditional rule-based autonomous systems due to the ability to understand complex instructions and interact with the user [21].

A. LLMs as a Core Component of Autonomous AI

Large Language Models (LLMs) are one of the fundamental building blocks of autonomous AI systems. These models offer enhanced cognitive abilities that make intelligent and independent system operations possible. LLMs are trained on massive collections of text from diverse sources. Through training, it acquires broad knowledge and language patterns. They can complete a wide range of jobs without the need for specific task scripting thanks to this thorough training [22]. LLMs help autonomous platforms perform complex tasks with minimal human intervention.

B. Advanced Capabilities of LLMs

LLMs support several important functions, including:

- **Reasoning:** Analyzing information and drawing logical conclusions.
- **Planning:** Creating action plans to achieve specific goals.
- **Decision-Making:** Selecting the most appropriate action among multiple alternatives.
- **Natural Language Understanding (NLU):** Understanding and interpreting human language effectively.

C. Transformer-Based Architecture

LLMs are built using Transformer architectures, which are designed to process large amounts of textual data efficiently. Transformers use attention mechanisms to identify relationships between words and sentences, enables LLMs to capture long-range contextual dependencies within language data.

D. LLM Inference Pipelines

It includes several steps that can be described by input pre-processing, tokenization [23], model inference, decoding, and output response generation. In the process of inference, user inputs are tokenized and fed to the transformer blocks, resulting in context-based outputs.

E. Retrieval-Augmented Generation (RAG)

It works to improve the capabilities of LLMs by merging the power of information retrieval methods with that of generative language models and its Illustrate in Table I [24]. In contrast to only leveraging the knowledge gained through training, RAG leverages information retrieval during inference time from sources outside of the training process, such as external databases or knowledge bases, and includes this knowledge in the generation step [25]. Thus, RAG allows for improved facts accuracy and hallucination reduction.

TABLE I. KEY COMPONENTS AND CAPABILITIES OF LARGE LANGUAGE MODELS (LLMs)

Technology	Function	Benefit to Autonomous AI
Advanced Capabilities	Reasoning, planning, NLU, decision-making	Intelligent autonomous behavior
Transformer Architecture	Context-aware language processing	Better understanding and response generation
Large-Scale Training	Learning from diverse datasets	Broad knowledge and task adaptability
Inference Pipeline	Input-to-output processing workflow	Real-time intelligent responses
RAG	Retrieval of external knowledge	Improved accuracy and reduced hallucinations

IV. MULTI-AGENT REINFORCEMENT LEARNING (MARL) FOR AUTONOMOUS INTELLIGENCE

The idea of reinforcement learning, which involves several agents working in a single environment and discovering their best strategy through a number of trials-and-errors exercises. Unlike reinforcement learning in which only one agent comes up with its own strategy independently of other participants [26], MARL implies that interactions among a few participants take place and that their behaviors affect both the environment and learning processes of other participants[27]. As a result, several issues arise associated with non-stationarity, partial observability, coordination, and communication. The introduction of deep learning techniques enabled agents to devise sophisticated strategies.

A. Paradigms in Multi-Agent Reinforcement Learning

It describes three primary ways that agents collaborate and learn in a communal setting:

- **Centralized learning:** involves sharing of information by the agents where all agents learn about the policies through the use of knowledge of the environment that is globally available to the agents.
- **Decentralized learning:** The agents get to learn individually from the observations obtained locally. This mode of learning is scalable but may require more coordination than centralized learning.
- **Centralized training with decentralized execution (CTDE):** The CTDE learning paradigm has proved to be the most popular one since it takes advantage of both decentralized and centralized modes of learning whereby agents learn through global information in training while executing tasks independently [28].

B. Multi-Agent Coordination and Competition

In MARL settings, agents are either cooperative, competitive, or some combination of both based on the goals aim to achieve. Cooperative agents Collaborate to optimize their reward functions and reach goals that are hard or even impossible to accomplish individually. Typical examples of such agents include multi-robot systems, automated vehicle fleets, and sensor-based distributed networks [29]. On the contrary, competing agents have opposing interests and objectives, where an advantage gained by one agent might be at the expense of others. Competitive MARL settings are common in games, economics, and cyber security among other applications. The combination of cooperation and competition requires agents to learn the dynamics of collaboration alongside achieving individual goals. Different interaction models pose different challenges such as coordination, communications, strategy optimization, and reaching equilibriums.

V. SELF-HEALING ARCHITECTURES

Automatically discovering, analyzing, and healing itself from faults using little or no human interaction in Self-Healing Architectures. This type of intelligent computing architecture operates based on the biological model, where continuously sense and adapt to any changes that happen in order to maintain system operation and availability [30]. The overall goal of a self-healing architecture is to increase system reliability, resilience, fault tolerance, and operational efficiency by being able to automatically recover from any faults. Self-healing systems play an increasingly crucial role in the context of autonomous AI systems due to increased complexity in distributed systems and potential software and hardware failures within cloud-based environments.

A. Fault Detection

Basic concepts in self-healing systems are Detection of faults [31], which provide methods to detect and diagnose the abnormality of the system's functionality. Fault detection requires constant monitoring of system components, performance indicators, logs, and parameters to detect any anomalies in the operation of these factors [32][33]. Once the anomaly has been identified, a fault diagnosis process determines the cause, location, and intensity of the fault. With artificial intelligence, the process of fault detection and diagnosis is significantly accelerated due to the capability to

monitor and analyze high volumes of data within a short time period.

B. Automated Recovery Mechanisms

It ensures the restoration of the normal functioning of a computer system following the detection and diagnosis of fault instances. This process involves the implementation of pre-set recovery procedures without the requirement for human involvement since such an approach would lead to an increase in downtime and delay in recovery [34]. The common techniques include restarting the affected services, reconfiguring resource allocation, workload balancing, container replacement, patching programs, and rolling back configurations. Within a cloud-native and distributed environment, automatic recovery may be accomplished by utilizing orchestration frameworks such as Kubernetes [35].

C. Predictive Maintenance with AI

Preventive maintenance that uses machine learning and artificial intelligence to identify potential problems before arise. While reactive maintenance focuses on resolving problems that arise from failure events, predictive maintenance uses AI technologies to analyze data such as sensor readings, system logs, performance measures, and historical data about operations to gauge the current state of equipment and forecast future failure events. With autonomous AI systems, predictive maintenance allows hardware, cloud-based systems, robotics, and industrial Internet of Things (IoT) devices to function without interruption by scheduling maintenance activities only when needed [36]. Predictive maintenance not only saves on maintenance costs and increases the lifespan of systems, but also makes self-healing possible through the integration of systems with self-healing architectures.

VI. LITERATURE REVIEW

This review of literature provides an insight into the current trends in agentic artificial intelligence, autonomous AI agents, self-healing architectures, and multi-agent reinforcement learning, stressing decision-making intelligence, security issues, cooperation, and learning abilities.

Jun (2026) explores future trends related to securing autonomous AI agents, including defensive measures, system resilience, effective monitoring practices, and governance of AI. Using innovative cryptographic solutions, learning-based security measures, and multilayer security approaches, can help prevent weaknesses and encourage innovation. Also, opportunities that can contribute to creating adaptive and explainable AI agents that work in complex environments [37].

Acharya, Kuppan and Divya (2025) Considers the basic principles, features, and approaches that underlie agentic artificial intelligence. Considers its practical use in the spheres of healthcare, finance, and adaptive computing systems, focusing on its real-life advantages. In addition to this, the paper discusses some ethical issues that arise in the process and offers possible solutions to these problems [38].

Yuan et al. (2025) Cooperative Multi-Agent Reinforcement Learning (MARL) concerns the learning of multiple agents to complete certain missions cooperatively which cannot be achieved by an individual agent. There has been much research that has proved its effectiveness in

applications like path planning, self-driving cars, voltage regulation, and algorithm configuration. This paper aims at increasing the efficiency of coordination [39].

Yin et al. (2024) Multiple agent systems (MAS) find application in practical situations, where many agents have to make decisions within a common environment. The paper focuses on basic concepts from game theory (GT) and machine learning (ML), which are further linked with contemporary developments in the area of multi-agent reinforcement learning (MARL). An in-depth view on MARL is presented by outlining its possibilities as well as obstacles [40].

Luke and Wilson (2023) focuses on self-healing architectures that rely on machine learning for real-time identification, diagnosis, and recovery from failures. This paper introduces a unique ML approach aimed at improving

the robustness of software engineering through self-healing capabilities [41].

Wen et al. (2022), Presents a new architecture referred to as Multi-Agent Transformer (MAT), which converts cooperative MARL into sequence modeling (SM). The approach makes a connection between MARL and SM using an encoder-decoder structure. This results in efficient sequential decision making with linear time complexity and a guaranteed monotonic improvement of performance [42].

Table II provides an overview of recent researches carried out in the area of autonomous AI agents and multi-agent systems, giving information on the areas of focus, technologies used, significant discoveries, weaknesses and areas for further research.

TABLE II. REVIEW OF RECENT RESEARCH ON AUTONOMOUS AI AGENTS, DECENTRALIZED INTELLIGENCE, AND MULTI-AGENT DECISION-MAKING SYSTEMS

Reference	Focus Area	Technologies	Key Findings	Limitations	Future Work
Jun (2026)	Security of Autonomous AI Agents	Cryptography, Monitoring Systems, Ethical AI	Proposed proactive defense and resilient AI architectures for secure autonomous agents	Limited adaptability to rapidly evolving threats and dynamic environments	Develop adaptive, explainable, and trustworthy security frameworks for autonomous agents
Acharya, Kupan and Divya, (2025)	Agentic AI Fundamentals and Applications	Agentic AI, Adaptive Systems	Demonstrated applications in healthcare, finance, and software systems	Challenges in goal alignment, resource constraints, and environmental adaptability	Design scalable and ethically aligned Agentic AI systems for complex real-world scenarios
Yuan et al., (2025)	Cooperative Multi-Agent Systems	Cooperative MARL	Improved collaboration among agents for real-world applications	Limited coordination efficiency in open and dynamic environments	Enhance collaborative learning and coordination strategies in heterogeneous environments
Yin et al., (2024)	Multi-Agent Reinforcement Learning (MARL)	Game Theory, Machine Learning, MARL	Provided a comprehensive survey of MARL and intelligent decision-making in MAS	Coordination complexity and scalability issues in large-scale environments	Develop efficient and scalable MARL algorithms for complex multi-agent systems
Luke and Wilson, (2023)	Self-Healing AI Architectures	Machine Learning, Autonomous Recovery Systems	Proposed ML-based frameworks for autonomous failure detection and recovery	Limited evaluation in large-scale and real-time systems	Develop scalable and real-time self-healing architectures for autonomous AI agents
Wen et al., (2022)	Multi-Agent Transformer (MAT)	Transformer Networks, Sequence Modeling, MARL	Introduced MAT with linear complexity and monotonic performance improvement	Generalization and robustness in highly dynamic scenarios remain unexplored	Investigate robust transformer-based architectures for diverse multi-agent environments

VII. CONCLUSION AND FUTURE WORK

Autonomous AI has turned out to be a revolutionary paradigm where intelligent machines are able to think, learn, perceive, plan and act independently. In this regard, the current survey covered the development of autonomous AI platforms based on the use of LLMs, MARL and self-healing designs. According to this survey, LLMs have the ability to support advanced capabilities in terms of reasoning, planning, natural language processing and decision making, while MARL promotes the development of collaborative intelligence and adaptive learning. Besides, self-healing approaches contribute to increasing system resilience and fault tolerance in an automatic manner. As a result of this study, researchers made some important advances related to autonomous agents, Agentic AI, cooperative learning and intelligent recovery. Therefore, all of these technologies are moving forward to creating smart and reliable autonomous systems able to solve real-world problems.

Future researches should pay attention to the creation of a unified framework including LLMs inference, MARL and self-healing capabilities in autonomous AI platforms. In this regard, further investigations should promote scalability,

explain ability, security, energy efficiency, and real-time adaptability of autonomous AI platforms, supporting trustworthy multi-agent collaboration and operation in dynamic and uncertain environments.

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