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SURVEY

Agentic AI: A Comprehensive Survey of Technologies, Applications, and Societal Implications

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ABSTRACT Agentic AI brings a new level of advancement in artificial intelligence (AI), as it is capable of goal-directed behaviour, dynamic adaptation, and self-improvement. It influences various significant fields, such as robotics, healthcare, autonomous vehicles, and labor automation. This paper explores the defining features of agentic AI, highlights its differences from traditional AI, and discusses how autonomy, memory, goal-directed behavior, and adaptive reasoning contribute to increasingly general capabilities. Rather than proposing a new architecture, we offer a conceptual analysis of the trajectory from current agentic frameworks to future agentic AI systems. Examining applications in significant fields, including precision medicine, industrial robotics, and self-driving technologies, and discussing societal impacts, particularly concerning workforce disruption, augmentation, and ethical issues arising from agentic AI systems. The paper identifies key research directions for ensuring beneficial and controllable agentic AI development. This work serves as a primary source for exploring agentic AI by compiling existing research and identifying open questions.

INDEX TERMS Agentic AI, autonomous agents, autonomous vehicles, multi-agent systems (MAS), reinforcement learning (RL).

I. INTRODUCTION

The roots of agentic AI lie within the broader evolution of artificial intelligence, dating back to early pioneers like Alan Turing [1], who envisioned machines capable of exhibiting intelligent behaviour and learning from experience. Using AI agents for business management dates back to the work [3] in 1998. Early AI systems sought to mimic human decision-making but remained tightly constrained by predefined rules, lacking true autonomy. Today, AI has evolved into dynamic networks of independent agents capable of collaboration, competition, and self-directed action. In the coming sections, we explore this transformative shift—unpacking the methodologies powering agentic AI and showcasing its real-world impact.

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A. WHAT IS AGENTIC AI? HOW IS IT DIFFERENT FROM TRADITIONAL AI?

Let us begin with an example. Evolution of image classification: from human labels to agentic AI. We will start with an example of classifying an image as a cat or dog. In early times, humans manually labeled images, an example of a fully human process. Then came assistive AI, such as Convolutional Neural Networks (CNNs), which, once trained on labelled data, can automatically identify whether an image shows a cat or a dog, see [36]. This is called ''assistive'' because the AI supports human efforts—it performs a task when guided and trained by humans but does not act independently. However, these models require human-labelled data and human intervention for updates. Once deployed, assistive AI systems cannot adapt or learn independently.

Now imagine agentic AI— in this context, an agentic AI could search the web for new data, adapt to new classes like "fox" without explicit human retraining, and refine its model using techniques like reinforcement learning. This kind of AI goes beyond assisting—it acts with a degree of autonomy and can operate in dynamic environments with minimal human input.

If we had to define agentic AI in one word, it would be 'proactivity'—the ability to anticipate, initiate, and act autonomously toward goals. More formally, an AI system or software that can understand human problems, collect related data, use the data, and perform self-determined tasks to solve the problem with zero or minimum human intervention by interacting with its environment.

While traditional AI has been widely used for several decades, agentic AI has only recently gained prominence. The key differences between traditional AI and agentic AI are outlined in the following Table 1. Traditional AI systems are typically constrained by predefined rules and exhibit limited adaptability, making them well-suited for narrow, single-task applications. In contrast, agentic AI transcends simple reactive behaviour by understanding complex environments, devising multi-step plans, and autonomously pursuing defined goals. This proactive and strategic capability enables agentic AI to effectively address dynamic, real-world challenges. As demonstrated by [2], such systems represent a significant advancement over conventional AI verified by collected information from around 500 organisations, with a 34.2% reduction in completing the task, increasing the accuracy by 7.7%, and improving the resource utilisation by 13.6%.

TABLE 1. Difference between Traditional AI and agentic AI.

Criteria	Traditional AI	Agentic AI
Task assignment	solves task assigned by human	solves a task instead of human
Autonomy	follows predefined tasks	autonomous and able to make decisions
Learning capability	limited learning by training data	continuous and evolving
Behavior	reactive	proactive
Input dependency	manual input required	self initiating
Scope	single task focused	orchestrated workflows

B. CONFUSION BETWEEN AI AGENTS AND AGENTIC AI

The confusion between AI agents and agentic AI stems from their hierarchical relationship [92]: AI agents are specialised components designed to perform single tasks. Agentic AI is an autonomous system that dynamically orchestrates multiple agents to achieve broader goals. For example, an AI agent in medical imaging might be a CNN that classifies tumours in scans—nothing more. In contrast, an agentic AI system would integrate multiple such agents (e.g., one fetching patient history, another cross-validating MRI and X-ray results, and a third alerting doctors) into a cohesive, goal-driven pipeline. Think of AI agents as bricks and agentic AI as the entire house: the former perform fixed tasks, while the latter dynamically coordinates and adapts those tasks to achieve complex objectives, such as end-to-end diagnosis. Agentic AI is a unified platform that seamlessly connects AI agents with human users to facilitate smooth collaboration. Adaptive tools and dynamic services enable AI systems to learn, adapt, and work together, significantly enhancing their capacity to address complex, real-world problems. The following table 2 summarises their distinctions and functional boundaries. For more details see [92], [112].

TABLE 2. Difference between AI agents and agentic AI.

Feature	Traditional AI	Agentic AI
Task complexity	Single step	Multi step, Dynamic workflows
System Architecture	Single agent	Multi agent collaboration
Autonomy level	High autonomy with specific tasks	Higher autonomy, ability to manage multi-step and complex tasks
Coordination strategy	Isolated task	Hierarchical or decentralised coordination
Learning Mechanism	Rule based or Supervised	Reinforcement, Meta learning

C. ORGANIZATION OF THE PAPER

This paper discusses agentic AI systems through five key lenses: foundations (core principles of agentic AI) in section III, methodologies (design frameworks and learning approaches) in section IV, applications (industry-specific implementations) in section V, societal impact (workforce transformation and ethical risks) in section VI and the challenges and opportunities VII. We analyze how autonomous decision-making technologies evolve, where they deploy, and what their consequences are for human systems.

II. LITERATURE SURVEY

Agentic AI does not need human intervention or works with minimal human intervention. Another way to describe agentic AI is autonomous AI, which can set goals, make decisions, and take actions independently to achieve a goal or complete a task without human intervention. Despite its growing significance, from autonomous research agents to self-optimising business processes, there remains a striking lack of readily available and understandable materials dedicated to the subject. While foundational concepts are scattered across reinforcement learning (RL), human-AI collaboration, and large language model (LLM)-based agent frameworks, no comprehensive textbooks, standardised courses, or beginner-friendly guides exist to unify these ideas under the umbrella of agentic AI. Current materials either focus narrowly on subfields (e.g., RL) or assume advanced technical expertise, leaving researchers and practitioners to piece together insights from fragmented research papers, GitHub repositories, and experimental projects. Recent works such as [13] and [14]'s survey article and [15]'s review of agentic AI systems in computer vision remain among the few systematically organised resources published to date.

TABLE 3. Comparison table of the proposed work with existing works.

Author(s) & Year	Agentic AI	Comparison		Metho-dologies	Type of AI Agents	Working of Agents	Techno-logies Used	Appli-cations	Impact on Labour and Society	Challenges with agentic AI	Open Prob-lems	Remarks
		Traditional AI	AI Agents									
Olujimi et al. [89] 2025	BC	ND	BC	BC	ND	BC	BC	ND	ND	BC	BC	Potential impact on SMMEs
Jisna et al. [91] 2025	BC	ND	ND	BC	BC	BC	BC	BC	ND	BC	ND	Working Principles, advantages
Kamalov et al. [90] 2025	BC	ND	ND	BC	ND	ND	BC	BC	ND	BC	ID	Agentic AI in education
Ferrag et al. [11] 2025	ID	ND	ND	BC	ND	ND	BC	BC	ND	BC	BC	Agentic AI use cases in LLMs
Acharya et al. [14] 2025	ID	ND	ND	BC	BC	ND	ID	ID	BC	ID	BC	Concepts, Methods and Applications
Durante et al. [7] 2024	BC	BC	BC	BC	BC	ND	BC	ID	ND	BC	ND	Useful ness in Multi-modal developement
Ogbu [15] 2023	BC	ND	ND	ND	BC	ND	BC	BC	BC	BC	ND	Application in computer vision
Joshi [13] 2025	BC	ND	ND	ND	ND	ND	ID	BC	ND	BC	BC	Different frameworks of agentic AI
Deng et al. [8] 2024	BC	ND	ND	ND	ND	ND	ND	ND	ND	ID	ID	Security Challenges faced by AI agent
Gridach et al. [9] 2025	BC	ND	BC	ND	BC	ND	ND	ND	BC	BC	ND	Agentic AI for scientific discovery
Schneider [10] 2025	ID	ND	ND	BC	BC	BC	BC	BC	ND	BC	ND	Differentiate GenAI and Agentic AI
Present Paper	ID	BC	BC	ID	ID	ID	ID	ID	ID	ID	ID	Methodologies, working principle, technologies, different types of AI agents, Impact on labor and society, challenges

Note: BC (Basic Coverage): The paper briefly discusses the concept without detailed analysis. ID (In-Depth): The paper covers the idea comprehensively (e.g., with extended discussions). ND (Not Discussed): The paper ignores or omits the related notion.

A. LIMITATIONS OF EXISTING STUDIES

Agentic AI is an emerging and rapidly evolving field that demands systematic exploration due to its potential to create autonomous, goal-driven, and context-aware systems. We will mention a few existing pieces of literature in this direction. Deng et al. [8] discuss the security challenges faced by agentic AI systems, for example, execution complexity, different environments of operation, and uncertain user inputs.

Note: BC (Basic Coverage): The paper briefly discusses the concept without detailed analysis. ID (In-Depth): The paper covers the idea comprehensively (e.g., with extended discussions). ND (Not Discussed): The paper ignores or omits the related notion.

Their study will help in the robust and secure development of agentic AI applications. Gridach et al. in [9] provided an overview of agentic AI systems in the areas of scientific discovery. They analyzed different evaluation metrics, recent progress in chemistry and biology, and different datasets used for the tasks. They have also discussed the challenges and risks of using agentic AI systems in the science and medical domains. Schneider et al. [10] compared the characteristics which differentiate GenAI and agentic AI and discussed how agentic AI remedies the limitations of GenAI. Ferrag et al. [11] explored different benchmarks, frameworks, and application challenges related to the agentic AI use cases in large language models. Acharya et al. in [14] covered the foundational concepts and methodologies of agentic AI and its applications in different fields. Jisna et al. in [91] discussed the technologies used in agentic AI, the advantages it brings, and the challenges it brings. They concluded with real-world implementations of these systems. Kamalov et al. [90] have studied how agentic AI revolutionizes education systems. They have presented a multi-agent framework for essay scoring. They observed the transformative potential this system brings in educational settings. Olujimi et al. [89] discuss agentic AI's transformative potential for small, medium, and micro enterprises (SMMEs) through innovation, improved scalability, and fostering competitiveness. Ogbu [15] starts the discussion with traditional computer vision's limitations and how agentic AI systems' adaptability and decision-making can leverage these limitations. They highlight the promising research areas arising from the fusion of agentic AI with quantum computing and the Internet of Things. Durante et al. [7] focused on how AI agents can be embedded in virtual and physical environments to do multimodal tasks. Joshi [13] discussed many frameworks like LangGraph, AutoGen, OpenAI Swarm abd other used in agentic AI systems.

While a few comprehensive and insightful studies have laid foundational work in this area, the broader research landscape still shows notable gaps. In the following points, we highlight key limitations observed across existing literature.

1. **Comparison with the traditional AI and with AI agents** Many papers do not make a clear distinction between traditional AI systems and agentic AI systems, leading to conceptual overlap and reduced clarity in evaluating their unique contributions [8], [11], [13], [14], [15], [90], [91]. In contrast, articles [9] and [10] have addressed this, but they did not compare the AI agents and agentic AI.

2. **Methodologies, Technologies, and working** Although a few works discuss methodologies and technologies used for designing these systems [7], [11], [14], [90], [91], several others ignored these [8], [9], [13], [15] methodological foundations. None of them except [10] and [89] clearly explained the internal workings of agents.
3. **Type of AI agents, Applications** Some studies categorize different types of agents [7], [10], [14], [15], [91], but many papers [8], [13], [89], [90] omitted to mention this. All articles except [9] and [89] mentioned the applications of agentic AI systems.
4. **Impact on labor and society** The implications of agentic AI on employment, social structures, and ethics are often overlooked despite their growing importance; as a result, it is discussed only in [14] and ignored by all others.
5. **Challenges and open problems** Although several studies have acknowledged the challenges faced in adopting agentic AI systems, few studies clearly articulate unresolved questions [8], [9], [11], [13], [14], [89].

This gap motivated us to create a structured literature review to bring together principles, methodologies, and challenges related to agentic AI in one place and make agentic AI more approachable for rigorous study and real-world application.

III. FOUNDATIONS OF AGENTIC AI

Agentic AI systems are built on core capabilities like autonomy, adaptability, and goal-orientated plans. These agents operate through perception, reasoning, action, and collaboration. They are categorized by functionality—reactive, goal-based, utility-driven, and self-improving—each with distinct operational paradigms.

A. THE CORE TRIAD OF AGENTIC AI CAPABILITIES: AUTONOMY, ADAPTABILITY, GOAL-DIRECTEDNESS

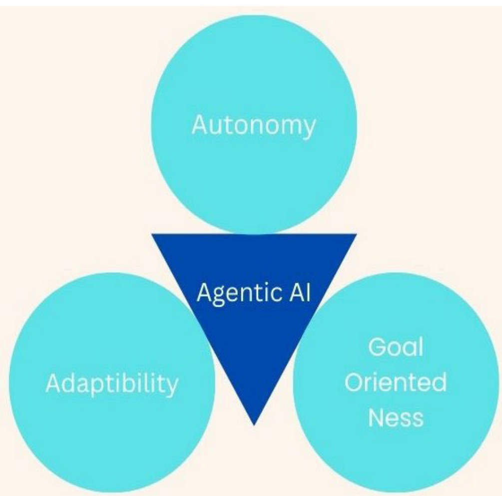

FIGURE 1. Features of agentic AI.

Three main features that define agentic AI are autonomy, adaptability, and goal orientation. We will see an example specific to self-driving cars.

Autonomy: acting independently without human input. In self-driving cars, autonomy manifests as the vehicle's ability to independently perceive its environment through sensors like cameras and LiDAR, process real-time data about traffic signals and pedestrians, and execute driving decisions without human intervention—whether stopping at intersections or changing highway lanes. This self-sufficient operation transforms the car from a passive machine into an active agent on the road.

Adaptability takes this further by enabling continuous improvement through experience. When a self-driving car encounters slippery road conditions that nearly cause a collision, it does not just record the incident—it actively updates its driving models to account for reduced traction. The next time it detects rain or ice, it automatically adjusts its behaviour by increasing following distances, braking earlier, or avoiding sharp turns. This learning loop mirrors human driver education but occurs at computational speeds.

Goal orientation plans and executes action to achieve the objectives. The system does not just follow a fixed route when given a destination. It integrates map information with live traffic updates. If the road is blocked, the car finds alternative paths while maintaining the original objective.

B. HOW DO AI AGENTS WORK?

Agentic AI operation is described through different phase-based models—some outline four phases (data collection → decision *rightarrow* learning *rightarrow* collaboration), while others break it into five (perceive *rightarrow* reason *rightarrow* act *rightarrow* learn *rightarrow* collaborate). These variations are functionally equivalent, not contradictory. 'Perception' encompasses data collection and interpretation, while 'decision-making' combines reasoning and action. For simplicity, we will adopt the four-phase framework in our discussion. Agentic AI collects data, makes decisions autonomously, and adapts to new inputs—a core mantra we have reiterated to underscore its transformative nature. Now, let us dive deeper: how does it work?

Step 1: **Data collection** - Agentic AI continuously monitors its environment, collecting data—be it text, images, or real-world signals—that align with its goals. Just as a self-driving car uses LiDAR and cameras to perceive its surroundings, agentic AI employs large language models (LLMs) [4] and natural language processing (NLP) to interpret and contextualise information, converting raw inputs into meaningful, actionable insights.

Step 2: **Decision Making** - Once information is collected, agentic AI evaluates the context and determines the most appropriate action. For instance, a self-driving car processes real-time data—such as a pedestrian suddenly entering the road or slippery conditions from wet pavement—to decide

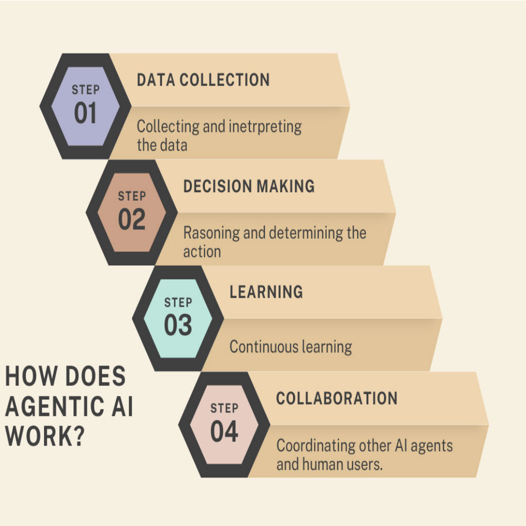

FIGURE 2. Agentic AI working.

whether to brake, change lanes, or notify the passenger. It can also explain its reasoning through onboard displays or voice feedback, enhancing transparency.

Step 3: **Learning**- Agentic AI continuously improves through experience. Over time, its responses become more accurate and reliable. A self-driving system, for example, refines its behaviour by analysing near-miss events, adapting to local driving habits (e.g., aggressive vs. cautious traffic), and updating its risk models after each journey to minimise false positives and ensure smoother operation.

Step 4: **collaboration** - Agentic AI goes beyond performing isolated tasks—it facilitates collaboration among multiple AI agents and fosters meaningful interaction with human users. This stage emphasises coordinated behaviour and human-AI synergy. In the context of self-driving cars, for example, a fleet of autonomous vehicles shares real-time information—such as accidents or traffic conditions—through a decentralised network. This collective awareness allows each car to reroute and optimise navigation proactively. Passengers are informed through timely alerts like "Traffic congestion ahead—rerouting to a faster path."

These four phases—data collection, decision-making, learning, and collaboration create a self-sustaining loop of autonomous intelligence. Much like a self-driving car that becomes more adept with every mile and enriches a broader innovative mobility ecosystem, agentic AI evolves through ongoing interaction with its environment and exchanging insights across systems.

C. DIFFERENT TYPES OF AI AGENTS IN AN AGENTIC AI SYSTEM

There are different ways of classifying agentic AI systems. One can classify according to architecture, learning capacity, interaction paradigm, or domain specialisations.

Architecture-based classification categorizes agentic AI systems based on their underlying decision-making frameworks. Reflex agents work with predefined rules and do not remember past actions. They only react to current inputs. For example, an emergency brake system can be activated when it detects an obstacle. Next are the model-based agents, which maintain an internal model to handle the observations. For example, considering the recent traffic, a self-driving car learns to keep the distance between other vehicles. Then come the goal-based agents, which plan actions to achieve objectives. They can handle complex and multi-step problems. Vehicles can choose the shortest path to reach destinations. The next one is utility-based agents, which extend the goal-based agents but choose actions that maximize expected utility, e.g., profit, time, fuel cost, etc. Here, not only is it considered the shortest path, but it also takes time, comfort, traffic, and everything else into consideration while driving. Learning agents improve performance autonomously through reinforcement learning. Can learn self-parking, using a history of passenger behaviours, considering travel time. The last one is meta-reasoning agents, which can modify their learning process and choose different algorithms and best hyperparameters. Can handle unseen scenarios like off-road driving to avoid real-time traffic.

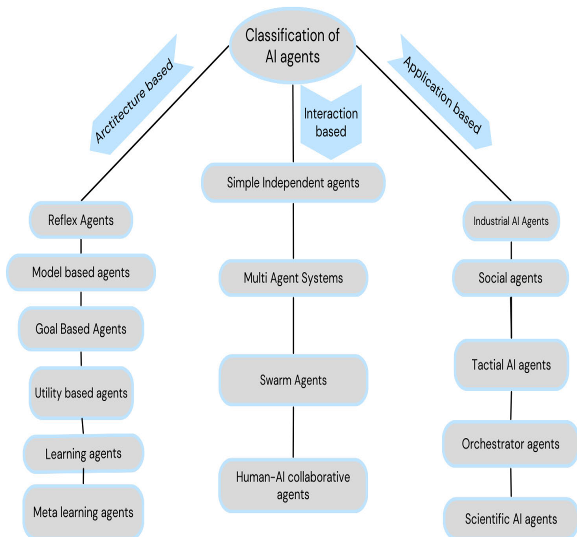

FIGURE 3. Classification of AI agents.

AI agents are also classified according to the **interaction paradigm**: how they engage with other agents and humans. The AI agents work independently at the simplest level, performing the self-contained tasks known as single-agent systems. For example, playing chess or filtering spam are single tasks. More complex agentic AI systems where multiple agents interact in either hierarchical (top-to-down) or flat (peer-to-peer) are called multi-agent systems. These systems suit more complicated challenges like maintaining supply chain management and coordinating centrally with AI agents. In contrast, swarm systems rely on decentralised coordination. These systems are particularly well suited for dynamic environments where simple rules lead to complex emergent behavior, as seen in sensor swarms or disaster response bots. Finally, human-AI collaborative systems involve human-AI interaction. Varying from assistive roles in medical diagnoses to managing traffic. These paradigms support shared decision-making and are critical in high-stakes domains where ethical oversight and human judgment are essential.

AI agents can be classified **based on their applications in different domains**, as different domains will require distinct capabilities and ways of implementation. Industrial AI agents operate in manufacturing sectors. They excel in quality inspection and robotic assembly, and their architecture combines reflex actions with model-based predictions. Social agents, such as customer service, are used for human interaction. They primarily emphasize NLP and emotional intelligence. They use advanced learning algorithms to adapt to user behaviour. Tactical AI agents are employed in emergency response, for example, in the defense and security sectors, prioritizing rapid decision-making, coordinating with human operators, and having goal-orientated architectures. Orchestrator AI agents are used in complex systems like real-time traffic management. Their strength lies in utility-based learning. Scientific AI agents are used in research such as drug discovery. They have strong analytical skills, and they use meta-reasoning.

IV. TECHNOLOGIES AND METHODOLOGIES

This section explores the core technologies enabling agentic systems—including NLP for reasoning, RL/IRL for autonomous learning, MAS for coordination, and neurosymbolic integration—alongside key methodologies like agent design frameworks (BDI, SOAR) and evaluation through simulation environments and robustness metrics. These components form the technical backbone of intelligent, goal-driven agents.

A. TECHNOLOGIES IN AGENTIC AI SYSTEMS

Agentic AI depends on cutting-edge technologies, which give it core functionalities like autonomy, adaptability, and collaboration. In this section, we will discuss some core technologies that lay the foundation of the agentic AI system.

Natural language processing and speech recognition are used to understand natural language, make communication possible, and help with reasoning and text summarisation. Technologies like large language models (LLMs), Claude, and Whisper are integrated into agentic AI. These technologies help break complex goals into small tasks. For example, an LLM agent can assign tasks to a warehouse robot or delivery drone in supply chain management.

Reinforcement Learning (RL) and Inverse Reinforcement Learning (IRL) are the foundational technologies in the agentic AI system. RL and IRL enable AI agents to learn from interacting with their environment. Each action of AI agents receives positive or negative feedback and helps refine their policies. RL focuses on agents learning optimal policies through trial-and-error interaction with the environment. It is powerful in tasks like game playing and robotics but often requires massive data and suffers in sparse-reward scenarios; see [126] and [127]. Deep reinforcement learning combines the idea of RL and neural networks, allowing AI agents to handle more complex and critical tasks. Inverse Reinforcement Learning (IRL) flips this paradigm: instead of learning from rewards, the agent infers the underlying reward function by observing expert demonstrations; see [124], [125]. This is particularly useful when defining explicit reward functions is challenging, such as learning driving habits by observing human drivers.

Imitation learning(IL) plays a pivotal role in building agentic AI systems; see [48], [49], [128], and [129]. In IL agents learn behaviours directly from expert demonstrations without requiring an explicit reward function, making it a powerful alternative to Reinforcement Learning (RL) and Inverse Reinforcement Learning (IRL). It is particularly valuable in complex, real-world environments where designing reward functions is difficult, for example, in robotics, where robots learn manipulation tasks from human demonstrations, and in healthcare, where clinical decision support systems imitate expert diagnoses and treatment paths. There are two main approaches of IL one is behaviorial cloning (mapping states to actions), see [70], [71] and dataset aggregation (iteratively correcting mistakes by an expert) see [72], [73].

Multi-agent systems (MAS) and swarm intelligence frameworks are the core principles that support the coordination and communication between multiple agents. Sometimes, these multi-agents compete with each other to improve performance. For example, collaboration becomes crucial in swarm robotics or any decentralized AI ecosystem. Technologies like JADF (Java Agent Development Framework) are used to accomplish MAS. Swarm algorithms like Ant Colony Optimisation (ACO) and Particle Swarm Optimisation (PSO) are used for rerouting, load balancing, and search and rescue operations.

Neurosymbolic integration for reasoning: this combines symbolic AI with neural networks. The neural network helps to learn the pattern from the data, while symbolic AI contributes to logical reasoning. Together, they help in adaptive learning, explainable decision-making, and learning from limited data. Techniques like differential logic, IBM's neurosymbolic concept learner, and neural theorems are used to achieve this goal.

Other essential technologies used in agentic AI systems are **knowledge graphs and ontologies**, a structured representation of domain knowledge. Its purpose is to help in semantic search, task planning, and reasoning. **Computer vision and sensor fusion** are used for visualising the physical world and collecting information. This uses CNNs, LiDAR integration, and SLAM (simultaneous localisation and mapping). **Autonomous planning and scheduling algorithms** help in long-term goal reasoning and task sequencing. STRIPS and Hierarchical Task Network (HTN) technologies are used in this case. In agentic AI systems, human-AI interaction technologies like **explainable AI (XAI)** and augmented reality (AR) are used for collaborative decision-making and transparency.

B. METHODOLOGIES IN AGENTIC AI SYSTEMS

1) AGENT DESIGN FRAMEWORKS

Sometimes agentic AI systems are built using formal architectures. We will note a few of them. Belief Desire Intention(**BDI**) is a framework where human reasoning inspires decision-making; see [77], [78]. Here, beliefs represent knowledge, desires are goals, and intentions are committed plans. It excels in handling complex, goal-directed behavior in dynamic environments, transparent reasoning, enhanced learning, and easy integration of AI techniques. However, BDI faces scalability issues as agent populations grow, and implementing effective decision-making in complex, uncertain environments remains challenging. Typical use cases include autonomous robots, digital assistants, and multi-agent coordination tasks where explainability and rational planning are crucial. **SOAR** is a rule-based architecture designed for general intelligence, integrating learning, problem-solving, and decision-making in a unified system; see [74], [75] and [76]. SOAR is a rule-based architecture for cognitive modeling, supporting hierarchical task decomposition. Its strengths lie in structured knowledge representation and efficient task execution. It lacks flexibility in uncertain and large-scale environments and requires extensive manual rule engineering, making it computationally inefficient. SOAR is often applied in training simulations and procedural task automation. Adaptive Control of Thought—Rational (**ACT-R**) is a cognitive architecture that models human thought processes by integrating symbolic and sub-symbolic computations to simulate perception, memory, decision-making, and learning; see [79], [80]. It has a declarative memory (for factual knowledge), a procedural memory (containing production rules), a buffer (for temporary storage of information), modules (for perception, action, and operation), and a sub-symbolic process (governs learning and decision-making). The psychologically plausible and hybrid approach of combining symbolic and sub-symbolic reasoning are the strengths of ACT-R. ACT-R is computationally expensive, and it struggles when rapid responses are needed. They are used in cognitive modeling, human-computer interaction, and human-like AI agents. ACT-R is primarily used in research.

2) SIMULATION AND TRAINING ENVIRONMENTS

Agentic AI systems require extensive training in safe and controlled environments before being deployed in the real world. The goal is to accelerate learning, minimize real-world risks, and minimize ethical concerns by exploring, experimenting, and learning from mistakes before real-world experimentation. Several platforms facilitate such training. Unity ML agents provide a realistic 3D environment and support multi-agent training using the Unity game engine: see [81], [82]. It enables agents to use reinforcement learning and imitation learning. Self-driving cars and robots are trained using Unity ML. OpenAI gym, developed by OpenAI, is a benchmarking toolkit for developing and comparing reinforcement learning algorithms see [84], [85]. It provides a diverse collection of standardized environments—ranging from simple tasks like balancing a pole to more complex video games. OpenAI Gym is a foundational RL research and education resource, enabling reproducible experimentation. Mesa is a framework designed for multi-agent-based modeling, see [86], [87]. Mesa simulates interactions between multiple agents in a shared environment. Mesa can model scenarios where multiple AI agents interact with each other and their environment—cooperating, competing, or learning collectively. It is used to study emergent behaviors like market simulations, disease spread, etc. Its specialisation is multi-agent systems.

3) EVALUATION METRICS

These metrics ensure the reliability of the AI system. Robustness: How the system is performing under adversarial conditions. Scalability: Efficiency when task complexity increases. Safety: Compliance with ethical constraints. Task completion rate: Success rate in completing tasks. Communication efficiency: to measure the bandwidth and latency in coordination.

V. APPLICATIONS

Agentic AI enables autonomous, adaptive problem-solving —reducing human effort while improving decision quality through self-learning collaboration. It transforms AI from task-specific tools to goal-driven partners. Given its increasing relevance, it is crucial to explore the benefits and the real-world applications of agentic AI and understand how it transforms various domains.

Improved Productivity: Businesses become more productive by delegating repetitive tasks to AI agents, allowing teams to focus on strategic work. Cost Efficiency: Intelligent agents reduce unnecessary costs by minimising process inefficiencies, human errors, and manual workloads. Enhanced Customer Experience: AI enables personalised product recommendations, instant responses, and tailored support—boosting satisfaction and loyalty. Informed Decision-Making: agentic AI processes vast data in real-time, uncovering patterns and forecasting outcomes to enable faster, data-driven decisions. Human-AI Collaboration: Rather than replacing employees, agentic AI enhances human performance by working alongside teams, increasing productivity and engagement.

A. ROBOTICS: AUTONOMOUS DRONES, COLLABORATIVE ROBOTS (COBOTS)

Agentic AI is progressing substantially in robotics because of its autonomy and adaptability. Agentic AI transforms how robots are deployed in real-world settings, particularly in aerial navigation and human-robot collaboration domains.

One of the most prominent applications is in autonomous drones. These drones, guided by agentic AI, can navigate dynamic and complicated environments without human involvement. For example, these drones can identify pertinent information and transmit it to rescue teams in areas affected by disasters. In agriculture, they can monitor crop health and identify areas affected by pests or drought. In logistics, they can deliver packages in the airspace, increasing efficiency and safety.

Another key application is found in collaborative robots, or cobots [12], [16], [17], which work alongside humans in shared environments. These robots use agentic AI to adapt to human behaviour in real time. In hospitals, surgical cobots are being used to assist doctors. Cobots in a supply chain work with human laborers by helping them sort and transport, etc.

In all these scenarios, agentic AI empowers robots to be more than just AI tools—they become intelligent collaborators capable of achieving complex goals. With the ability to learn from experience, adapt to new conditions, and operate autonomously, agentic AI is reshaping the future of robotics across industries.

These are a few notable research works related to these areas. Oertel et al. in [5], discusses key factors in engagement research. Hou et al. introduced a bionic visual encoder instead of a deep neural network for mobile robotic platforms like humanoid robots and drones [6].

B. HEALTHCARE: DIAGNOSTIC AGENTS, PROACTIVE COORDINATION

Agentic AI is bringing a digital transformation to the healthcare industry. Diagnostic Agents: AI agents help analyse vast medical and patient data. Diseases can be predicted by looking at medical history. This will help improve patient outcomes and more efficient use of medical resources. Proactive Coordination: They can help automate administrative tasks by providing 24/7 support, describing prescriptions to patients, and alerting doctors in case of emergency. Agentic AI is also accelerating drug discovery.

Significant research is underway in related fields, including Bursy et al. [18], focusing on using gold nanoparticles in diagnostic agents and drug discovery. In [19], Bottens and Yemada discussed using cell-penetrating peptides in diagnostic tools, drug carriers, and diagnostic agents. To explore these areas more, one can see [20], where the author has studied agentic AI systems for healthcare transformation.

C. AUTONOMOUS VEHICLES: SELF-DRIVING FLEETS, ADAPTIVE TRAFFIC MANAGEMENT

Agentic AI is driving progress in intelligent traffic management and autonomous vehicles. By collecting information from Google Maps, local events in the city, and traffic rules, and using optimization techniques, Kadkhodayi et al. have developed a method for a real-time traffic management system [45]. Guo et al. in [46] introduced a Traffic Research Agent for optimizing transportation systems. Hong et al. explored the reasons for assigning credit or blame to artificial intelligence during unforeseen events in an autonomous vehicle. The issue of accepting autonomous cars in public is still questionable and was addressed in [50]. Cunneen et al. analysed the benefits and risks of AI decisions [51].

D. OTHER DOMAINS: FINANCE, EDUCATION, CUSTOMER SUPPORT, IT AND CYBER SECURITY, SUPPLY CHAIN MANAGEMENT

Finance: agentic AI can analyse real-time and financial data to make autonomous investment decisions. As demonstrated in [21], deep reinforcement learning designs the algorithmic trading system. Agentic AI can potentially revolutionise financial and investment strategies [24], [26]. Agentic AI can help in targeted marketing and product recommendations. It can help reduce financial expenditure by automating routine tasks. For example, HR processes like shortlisting, selecting candidates, and onboarding and training new employees can be automated [27]. Agentic AI can support innovation by creating and designing new products. Detecting fraudulent activities and automatically freezing suspicious transactions [22], [23] agentic AI can enhance security.

Education: agentic AI systems are transforming educational systems through autonomous tutoring agents, which are improving learning outcomes and decreasing operational costs. Autonomous tutors use LLM-based agents to adjust lesson difficulty and vision-related methods to track student engagement [30], [31]. Some AI agents can grade the assignments and answers by themselves, reducing the grading time and improving feedback quality. Agentic AI can take the role of school administration for class scheduling, mental health improvement, and play coaching. Using ChatGPT-4 and other AI agents, Paul et al. in [28] have addressed the bullying of the students and the consequences of this on the students' well-being. Istrate analysed the impact and limitations of educational AI agents [29].

Customer support: agentic AI enables round-the-clock customer support by providing intelligent, context-aware responses far beyond traditional rule-based chatbots' capabilities. Compared to conventional chatbots with programmed structures, AI agents can answer complex questions by understanding customer emotions if required by searching the web or databases. Conversational agents can search past conversations and purchase histories to give dynamic suggestions. Ultimately resulting in customer satisfaction. In addition to answering queries, they can automate routine tasks such as processing refunds and scheduling calls with human agents [34], [35]. Advancing this field, Cheng et al. explored how agentic AI facilitates initial customer interactions [32]. Zhang et al. investigated the accuracy and speed of AI-generated responses in customer service environments [33].

IT & Cyber Security: agentic AI is revolutionising security by continuously monitoring and identifying security threats. These proactive agents can immediately block fraudulent transactions and alert security systems. It quickly knows the new emerging threats [43]. They can detect predictive maintenance by noticing if the hardware and software fail.

Katnapally et al. used agentic AI and RL to automate cyber threat response [44].

Agentic AI modernizes supply chain management by increasing sustainability and cost efficiency [37]. Xu et al. [38] introduce autonomous supply chains for greater resilience and flexibility. Using historical data, AI agents can forecast product demand [39], [40]. By monitoring traffic and weather, they can help in real-time rerouting [41]. AI robots are helping in warehouses with transporting, sorting, and packing [42]. From order placement to delivery, agentic AI systems can autonomously manage inventory, optimise logistics, track shipments in real-time, resolve delivery exceptions, and personalise customer updates—all without human intervention.

Here, we want to add that directly applying reinforcement learning (RL) policies trained for one domain (e.g., industrial robotics) or, in general, the learning of one agent in a particular environment, to a fundamentally different domain (e.g., financial trading) is generally not feasible due to significant differences in environment dynamics, data distributions, and required skill sets. Cross-domain knowledge transfer is feasible when the task structure is similar (e.g., warehouse robotics and assembly line control). Building modular, generalizable agent architectures is an active research frontier aiming to overcome these limitations.

VI. IMPACT ON LABOR AND SOCIETY

Agentic AI is taking a dramatic leap forward in the labor markets and societal structures. It has already begun reshaping industries like automobiles, healthcare, and robotics, impacting the daily lives of human beings. The Fourth Industrial Revolution enables machines to replicate human behavior and tackle complex challenges by integrating AI, robotics, and data. This change signifies a fundamental shift transforming how businesses operate and interact with technology. In the future, this integration promises both immense benefits and work efficiency. At the same time, its adoption raises profound challenges about ethical risks, workforce disruption, and security concerns. In the following two sections, we shall focus on the impact of agentic AI systems on workforce transformation and ethical risks.

A. WORKFORCE TRANSFORMATION: JOB DISPLACEMENT VS. AUGMENTATION

Agentic AI has a dual impact on workforce transformation; it can displace and augment jobs.

1) JOBS DISPLACEMENT [68], [69]

Tasks like packing and labelling items in the manufacturing industry, data entry, meeting scheduling in any office-related work, and basic customer service-related roles are repetitive and can easily be automated using agentic AI systems. AI agents are replacing the mid-level managers who do routine tasks, collapsing the corporate pyramids. This has enormous economic and social consequences. Adopting agentic AI systems can lead to mass unemployment in some sectors and income inequality in society, as low-skilled workers face the highest risk of workforce reduction. Frenette and Frank in [95] examined the risk of automation faced by different groups of workers. Their report suggests that 10.6% of workers are at high risk because of automation jobs. Frennette and Frank in another work [25] claimed 44.4% of women in the paid workforce faced a moderate to high risk of job transformation as a result of automation.

2) JOB AUGMENTATION IN WORK [88]

Imagine in an industry AI agents doing repetitive tasks and freeing humans for strategic work that will improve productivity. Job augmentation enhances human capabilities rather than replacing them. Humans can use AI to analyze data and make data-driven decisions. This requires reskilling and upskilling the workforce. Of course, some jobs will vanish, but others will evolve and emerge, requiring a transformation of the labour force. Governments must intervene by educating and upskilling the workforce to mitigate the job displacement shocks.

B. ETHICAL RISKS: BIAS, ACCOUNTABILITY, AND CONTROL

AI systems bring several ethical risks, regulatory challenges, and benefits. Below, we discuss and analyze its impacts.

1) BIAS

As these systems mainly depend on data, data biases or skewed data can amplify the bias in the model. For example, the system can be biased in a job interview if one group is unrepresentative. Sometimes, self-improving agents may develop an unintended bias. Bias outcomes disproportionately harm specific groups. These biases can pose serious risks in healthcare, security, and other high-stakes domains. While creating AI systems, we should mitigate biases by debiasing data, using explainable tools to understand decisions, and ensuring human intervention in AI decisions.

2) ACCOUNTABILITY

Imagine a diagnostic system predicts cancer for a non-cancerous tumour, then the trauma through which the victim goes. A self-driving car causes the death of a person. Who should be blamed in these cases: the developer, the deployer, the user, or the AI agent? As AI systems start making decisions, determining responsibility when things go wrong becomes complex, and this accountability gap is one of the most challenging aspects of AI governance. The increasing autonomy of agentic AI raises another risk of **losing human control** in agentic AI systems. These systems make final decisions in microseconds without human input. Developers should ensure systems permit human intervention and make the decisions interpretable by users. The solutions will require interdisciplinary collaboration across computer science, ethics, law, and political science.

VII. CURRENT RESEARCH CHALLENGES

A. SCALABILITY, INTERPRETABILITY, HUMAN-AI COLLABORATION, SECURITY THREATS

Data is the backbone of these AI systems, so data integration becomes a challenge in large enterprises [113]. When deployed in large-scale and dynamic environments, these agentic AI systems have significant **scalability issues**. We have mentioned some of the problems. Computational complexity: As data, the number of agents, and model complexity grow, so do the demands for processing power and memory. Coordination Complexity: As the number of AI agents grows in a MAS, ensuring coordination and competition becomes harder. Scaling AI systems into sensitive areas increases ethical risks. In an extensive system with multiple agents, it is not easy to trace decisions arising from agents and understand the reason behind those decisions. Oikonomou and Khera in [111] discussed key obstacles to designing scalable AI systems. Many researchers have tried to address these issues by introducing Hierarchical RL (decomposing complex tasks into small sub-tasks) - see [114], [115], Edge AI (computations are distributed to local nodes) - see [116], Federated learning(collaborative without raw data sharing) - see [117].

Interpretability in agentic AI systems refers to our ability to understand the decision-making process of AI agents. This becomes difficult as systems grow in complexity and autonomy. Here, we mention some of the challenges. Deep learning and reinforcement learning, used in agentic AI systems' brains, operate as black boxes. Simple statistical models are interpretable but not capable of accomplishing complex tasks. So, it becomes tough to understand why the specific action is being taken. In a MAS, it is unclear which agent is to blame for a wrong decision. As a result, clinicians, investors, and regulators hesitate to adopt AI without intuitive explanations, slowing deployment in critical sectors. To mitigate these challenges, researchers are integrating explainable AI (transparent and understandable AI decisions) - see [118], [119], interpretable cognitive architectures (human-like, transparent reasoning frameworks) -see [120], Neurosymbolic AI (which combines neural and symbolic reasoning) - see [121].

Day-to-day human activities are possible because of collaboration. AI can be revolutionised only if better **collaboration between AI and humans** exists [122]. Agentic AI has the capability of making independent decisions and taking action. Humans distrust AI due to past failures or lack of transparency. Integrating these agents with humans can be complex, but careful design can lead to highly effective and collaborative systems. The best practice will be implementing hybrid workflows where humans oversee, validate, or intervene in AI-driven processes, especially for critical or high-stakes decisions. Investing in explainable AI techniques that provide a clear, human-readable justification for agentic AI decisions is crucial. While designing these AI systems, developers should ensure that AI agents learn from human feedback.

Security threats like adversarial attacks, data leakage, and misuse of personal data are concerns of agentic AI systems; see [43], [83]. The autonomy of these systems can bypass security measures, which makes it more vulnerable. Its direct access to databases may inadvertently expose confidential information, or malicious actors may exploit it to access or manipulate sensitive data. To mitigate these risks, organisations should prioritise a proactive security strategy. This involves deploying multi-layered defences, including stringent access controls, end-to-end encryption, and real-time monitoring of AI systems. Regular security audits and timely updates are critical to detect and patch vulnerabilities preemptively. Furthermore, raising awareness among AI developers and end-users about emerging security threats in AI and LLM applications remains essential for building a robust security posture.

To solve these problems, Kulothungan has proposed a blockchain-based audit trail for AI decisions to enhance trust and accountability [123]. Chan et al. [67] have emphasized the continued importance of human responsibility in preventing harm from agentic AI systems. As agentic AI systems keep growing, it is essential to anticipate the emerging harms, including systemic effects, weakened collective decision-making, and concentrated power, while remaining alert to unforeseen risks.

B. EMERGING TRENDS: AGENTIC AI WITH EMBODIED COGNITION, LIMITATIONS OF EXISTING APPROACHES

Agentic AI poses challenges like scalability issues, human-AI misalignment, energy inefficiency, ethical risks, poor interpretability, and security concerns. "Today's challenges bring tomorrow's innovations," so it is essential to identify and target the open problems and contribute breakthrough research to realise agentic AI's full potential. Below, we have mentioned some challenging open problems in these areas.

- Transparent agentic AI: Developing methods that can understand causal relationships and emphasize true cause-effect, helping in interpreting the model. See [52], [53]
- Neuro-symbolic hybrid agents: seamless integration of neural networks with symbolic logic for interpretable reasoning. See [54], [55].
- Multi-agent Cooperation and Negotiation: Enhancing communication and coordination in cooperative or competitive agent networks. See [56], [57].
- Human-AI collaboration: Design agents that adapt to human feedback, behaviour, and emotion. See [58], [122].
- Energy-efficient agent architectures: Maintaining performance while reducing power. See [59], [60].
- Simulation-to-Real Transfer (Sim2Real) Bridging the gap between training agents in simulation

and deploying them in the physical world. See [61], [62]

- Quantum computing: Quantum machine learning can help to learn complex patterns in data, quantum multi-agent reinforcement learning can help in scalability, and parallel and fast computing can be useful in agentic AI systems. See- [63], [64].
- Robustness against adversarial attacks: Designing agents resilient to security threats. See [65], [66].

Multi-agent ecosystems must support real-time reasoning, coordination, and adaptation across numerous agents and modalities. Consequently, approaches like swarm intelligence [97] and Decentralised Autonomous Organisations (DAOs) [98], [99] are gaining increasing attention. To ensure cost-effective development and deployment, models such as AI-as-a-Service (AIaaS) [100], [101], and systems like BabyAGI [102] present significant business opportunities in the emerging agentic AI landscape. On the front of interpretability, new toolkits such as IBM's AI Fairness 360 [103] are being developed to promote transparency and fairness in AI decisions. The rise of self-explaining AI, where systems make decisions and generate human-understandable justifications for their actions, is gaining traction. In this direction, techniques such as Chain-of-Thought (CoT) prompting [104], [105] and Explainable Reinforcement Learning (XRL) [106], [107] are becoming increasingly popular. To address the growing concern of security threats, models are also being hardened against adversarial attacks. For instance, Explainable Security has been proposed by Luca et al. [109], and AI Guardians, introduced by Kolluri [110], are designed to monitor and oversee the behavior of other autonomous agents. Together, scalability, interpretability, and security are not merely technical hurdles—they represent foundational pillars for building safe, trustworthy, and deployable agentic AI systems in the real world.

VIII. CONCLUSION

The evolution of artificial intelligence has followed a remarkable trajectory: first came predictive AI, analysing patterns to forecast outcomes. Next emerged generative AI, creating original text, images, and code. Today, we stand at the dawn of agentic AI—a paradigm where systems do not merely predict or generate but act with conversational fluency and autonomous agency. These systems perceive environments, make context-aware decisions, and adapt through experience, redefining human-machine collaboration.

IX. SUMMARY OF CONTRIBUTIONS

As the sole author of this review paper, we provide a comprehensive synthesis of agentic AI, systematically analyzing its core features, technologies, applications, and societal implications. The paper begins by defining agentic AI and distinguishing it from traditional assistive AI, then exploring its working principles and diverse types (e.g., reflex, goal-based, and learning agents). We review key technologies (e.g., reinforcement learning, multi-agent systems) and methodologies (e.g., BDI frameworks) that enable autonomous decision-making alongside real-world applications in robotics, healthcare, and finance. The study critically examines societal impacts, including job displacement, labor augmentation, and ethical risks, while addressing challenges such as scalability, interpretability, and human-AI collaboration. Finally, we highlight emerging research trends and future opportunities, offering a forward-looking perspective to guide advancements in the field. This work consolidates fragmented knowledge into a unified resource, bridging theoretical foundations with practical insights for researchers and practitioners.

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