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A Survey on Machine Learning Techniques for Building Advanced Agentic AI Systems

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Abstract: *Agentic Artificial Intelligence (Agentic AI) represents an emerging paradigm in artificial intelligence that enables systems to operate autonomously, adapt to dynamic environments, and pursue complex goals with minimal human intervention. Unlike traditional AI systems that rely on predefined rules and supervised execution, Agentic AI integrates perception, reasoning, learning, and action to make intelligent decisions in real time. This paper presents a comprehensive survey of Agentic AI systems, focusing on their architectural foundations, learning paradigms, and emerging application domains. The study examines key architectural frameworks, highlighting their capabilities and limitations. The paper also reviews recent advancements and applications of Agentic AI in manufacturing, cybersecurity, healthcare, enterprise automation, and distributed systems. A comparative analysis of existing literature identifies critical research gaps related to scalability, explainability, security, governance, and human–AI collaboration. This survey provides a structured overview of the current state of Agentic AI and serves as a valuable reference for researchers and practitioners seeking to understand its architectures, capabilities, and application potential.*

Keywords: Agentic AI, Autonomous Agents, Multi-Agent Systems, Reinforcement Learning, Intelligent Systems, Adaptive Learning, Decision-Making.

I. INTRODUCTION

Artificial Intelligence (AI) has evolved significantly over the past decade, progressing from rule-based systems and narrow machine learning models to advanced generative and autonomous intelligence. While traditional AI systems excel at performing predefined tasks within constrained environments, they often struggle when confronted with dynamic situations that require continuous adaptation, long-term planning, and autonomous decision-making. These limitations have driven the emergence of Agentic Artificial Intelligence (Agentic AI), a new paradigm that extends AI capabilities beyond passive assistance toward proactive, goal-oriented behavior. Agentic AI refers to intelligent systems capable of perceiving their environment, reasoning about objectives, formulating plans, and executing actions autonomously to achieve complex goals with minimal human supervision [1]. Unlike conventional AI models that operate within fixed instructions, Agentic AI continuously adapts to changing conditions, manages resources, learns from interactions, and coordinates actions to accomplish multi-step tasks. This ability enables agentic systems to function effectively in uncertain and dynamic environments where predefined rules alone are insufficient.

The growing interest in Agentic AI is largely driven by the increasing demand for intelligent systems that can operate in real-world scenarios characterized by complexity, uncertainty, and rapid change [2]. Applications such as healthcare management, disaster response, cybersecurity, autonomous transportation, smart manufacturing, and enterprise automation require systems that can independently analyze situations, make informed decisions, and respond appropriately without constant human intervention [3]. By combining autonomy, adaptability, and goal-directed reasoning, Agentic AI has the potential to enhance operational efficiency, improve decision quality, and support human experts in high-stakes environments [4][5]. Recent advances in large language models, reinforcement learning, multi-agent systems, and multimodal intelligence have accelerated the development of agentic systems capable of planning,

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collaboration, and continuous learning [6]. As these technologies mature, Agentic AI is expected to play a crucial role in the next generation of intelligent systems, enabling more effective human–AI collaboration and expanding the scope of autonomous decision-making across industries. This paper presents a comprehensive survey of Agentic AI, focusing on its architectural foundations, learning paradigms, core capabilities, and emerging applications. In addition, recent research developments, challenges, and open issues are analyzed to provide a structured understanding of the current state and future potential of Agentic AI systems.

A. Paper Structure

The remainder of this paper is organized as follows. Section II presents an overview of Agentic AI, including its concepts, working principles, architectures, and key capabilities. Section III discusses the major learning paradigms. Section IV reviews the AI and machine learning approaches used to enable autonomous and adaptive agent behavior. Section V summarizes recent literature and highlights current advancements in the field. Section VII concludes the paper and outlines future research directions.

II. OVERVIEW OF AGENTIC AI

Agentic AI refers to AI systems that not only answer prompts but also set sub-goals, choose tools, and take multi-step actions to achieve a user's objective with limited supervision. In practice, these systems coordinate multiple agents, each handling part of the job, and an orchestration layer that keeps them aligned with the goal. An agent is a system that senses its environment, decides what to do, and takes action to achieve a goal. A simple example is a travel planner agent: Given 'plan a 3-day trip to Chicago under USD 1500', it breaks the task into subtasks such as flights, hotel, itinerary, queries real-time sources, compares options, books reservations, then produces a shareable plan that asks for confirmation only at key steps. This goes beyond traditional chatbots by planning, acting, and verifying outcomes in a loop. The term AI agent refers to an autonomous software entity that perceives, reasons, and acts to complete specific adaptively directed tasks. The term agentic AI refers to a multi-agent system where specialized agents collaborate, coordinate, and plan to achieve complex, high-level objectives. The difference in these terms for the flight booking example is shown in Fig. 1.

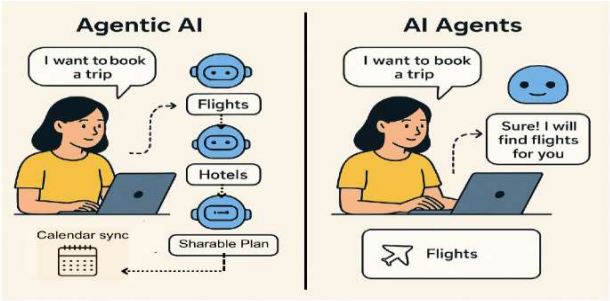


Figure 1: Agentic AI vs. AI Agents [7]

Interest in agentic AI is rising quickly as organizations look for automation that impacts real work, not just content generation. Industry analysts now track "AI agents" as a distinct market, estimating ~USD 5.3–5.4B in 2024 and projecting ~USD 50–52 B by 2030 (≈41–46% CAGR), reflecting strong enterprise demand for agents that can reason, use tools, and execute workflows [8].

A. How Do AI Agents Work

Agentic AI operation is described through different phase-based models—some outline four phases (data collection → decision right arrow learning right arrow collaboration), while others break it into five (perceive right arrow reason right arrow act right arrow learn right arrow collaborate). The working of agentic AI is shown in Fig. 2.

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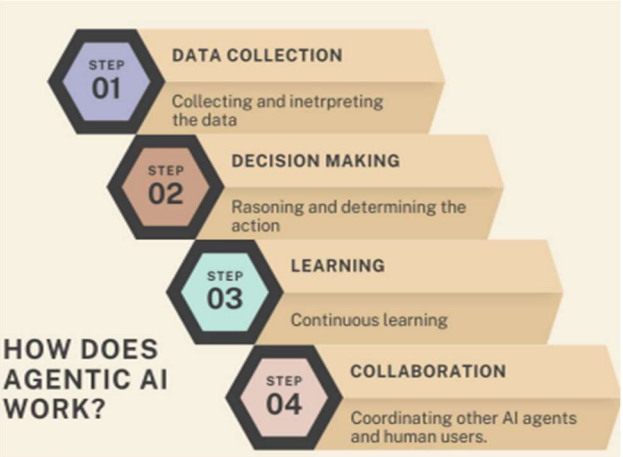


Figure 2: Agentic AI Working

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)[9]and natural language processing (NLP) to interpret and contextualize 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 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 behavior by analyzing near-miss events, adapting to local driving habits (e.g., aggressive vs. cautious traffic), and updating its risk models after each journey to minimize 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 emphasizes coordinated behavior and human-AI synergy.

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 [10].

B. Architectural Foundations of Agentic AI

Contemporary agentic systems are usually built on transformer architectures. Rather than a single prompt-to-response interaction, these systems operate in a continuous loop [11]. They sense the environment, plan the next steps, act with tools, observe outcomes, and then learn or revise their plan. The overall interaction cycle is illustrated in Fig. 3, which visualizes the agentic loop of sensing, planning, acting, observing, and learning under human oversight.

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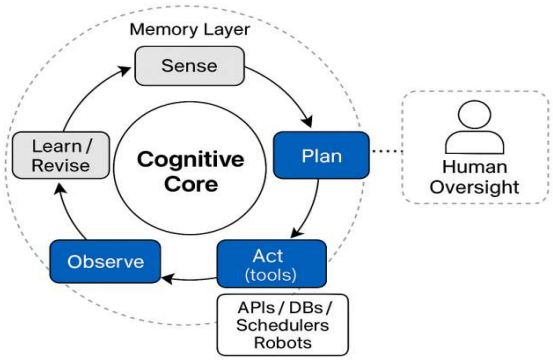


Figure 3: Agentic AI Interaction Cycle

The cognitive core creates plans and breaks goals into smaller tasks. A memory layer preserves context, previous actions, and user preferences [12]. The action interface connects the agent to external tools such as application programming interfaces (APIs), search engines, databases (DBs), schedulers, or robots and returns observations to the model. At the heart of the agent's control flow is the sense–plan–act–observe–learn loop shown in Fig. 2. The agent senses the current state, plans the next step in its cognitive core, acts through the appropriate tool, observes the returned outcomes, and then learns from the ensuing feedback to revise its plan. A memory layer preserves context and prior actions so behavior remains consistent over time, while human oversight monitors pending actions and enforces approval where needed. This disciplined loop supports goal-directed decisions with minimal human intervention and keeps the system aligned with stated objectives. Table 1 shows various architectures in agentic AI

Table 1: Comparison of Architectures in Agentic AI Systems

Architecture	Core Principle	Key Components	Capabilities	Applications	Advantages	Ref
Cognitive & Modular Architectures	Divide complex processes into specialized modules for reasoning, planning,	Knowledge representation, symbolic reasoning, neural learning, planning units	Perception, reasoning, adaptive goal-driven behavior	Robotics, autonomous decision support, industrial automation	High scalability, customization, and flexible module upgrades	[13]
Multi-Agent & Distributed Architectures	Use collaborative networks of autonomous agents that communicate and coordinate to achieve shared goals.	Agent communication protocols, coordination mechanisms, negotiation frameworks	Real-time multi-agent decision-making, distributed control	Smart grids, traffic optimization, financial forecasting	Scalability, parallel processing, and cooperative resource sharing	[14]
Reinforcement Learning-Based Architectures	Learn optimal strategies through trial-and-error and feedback-driven adaptation.	Reward-based feedback loops, Deep RL, policy-gradient algorithms	Adaptive learning, autonomous planning, proactive decision-making	Robotics, personalized recommendation systems, adaptive control systems	Continuous improvement, adaptability, and minimal human intervention	[12]
Hybrid Architectures	Integrate symbolic reasoning with data-driven	Knowledge-driven models, neural networks,	Structured reasoning with	Healthcare, enterprise AI,	Combines symbolic AI accuracy with	[14]

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	learning for adaptive intelligence.	contextual inference modules	contextual flexibility	intelligent assistants	neural learning efficiency	
Hierarchical Architectures	Organize decision-making into multiple layers for optimized control and adaptability.	Low-level perception layers, mid-level planning, high-level reasoning modules	Management of complex multi-stage tasks and dynamic goals	Autonomous vehicles, medical diagnostics, industrial robotics	High precision, interpretability, and faster task execution	[15]
Integrated Agentic Systems	Combine multiple architectures to maximize autonomy and adaptability.	Cognitive modules, multi-agent control, RL policies, hybrid reasoning layers	Self-evolving and goal-driven autonomy across environments	Multi-domain AI, AI governance frameworks, next-generation enterprise systems	Highest adaptability, real-time learning, and resource optimization	[12]

C. Agentic AI Capabilities: Autonomy, Adaptability, Goal-Directedness

AI systems are built on core capabilities like autonomy, adaptability, and goal-oriented plans. These agents operate through perception, reasoning, action, and collaboration. They are categorized by functionality—reactive, goal-based [16]. Three main features (see Fig. 4) that define agentic AI are autonomy, adaptability, and goal orientation. An example specific to self-driving cars.

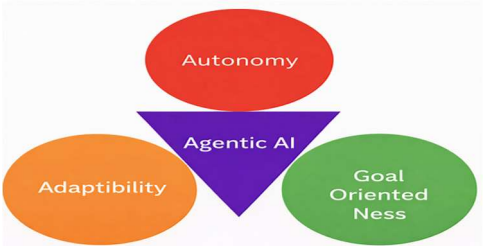


Figure 3: Features of Agentic AI

Autonomy

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

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 behavior by increasing following distances, braking earlier, or avoiding sharp turns. This learning loop mirrors human driver education but occurs at computational speeds.

Goal Orientation

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 [10]. We have reiterated to underscore its transformative nature.

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III. LEARNING PARADIGMS

Agentic AI relies on several learning paradigms, each suited to different types of tasks and goals. The main paradigms used in agentic systems are supervised, unsupervised, and reinforcement learning. Comparison of learning paradigms for agentic AI as presented in Table II.

Table 2: Learning Paradigms for Agentic AI

Learning Paradigm	Description	Suitability for Agentic AI
Supervised Learning	Learning from labeled data to map inputs to predefined outputs.	Useful for specific tasks such as classification and prediction but lacks adaptability for complex, dynamic goals.
Unsupervised Learning	Identifying hidden patterns, structures, and relationships in unlabeled data.	Provides insights and knowledge discovery but often requires reinforcement learning for goal-directed behavior.
Reinforcement Learning	Learning through trial-and-error interactions with the environment using rewards and penalties.	Highly suitable for Agentic AI due to its adaptability, autonomous decision-making, and goal-oriented behavior.

A. Capabilities and Limitations of Agentic Systems

This systematic review identified key capabilities and limitations across the agent types in our taxonomic framework. This section analyzes these dimensions, highlighting both the progressive enhancement of capabilities and the persistent challenges that remain.

Perception Capabilities

Perception capabilities have evolved significantly across agent generations, from simple sensor processing in reactive agents to sophisticated multi-modal understanding in contemporary systems.

- Limited to predefined feature extraction from structured inputs, typically operating on low-dimensional sensor data or symbolic representations. These agents struggle with ambiguity, noise, and novel perceptual patterns.
- Limited Memory and Model-Based Agents incorporate temporal context and learned feature representations, enabling more robust perception in noisy environments [17]. These agents can recognize patterns across time and adapt perceptual processing based on experience.
- Goal-Driven and Theory of Mind Agents demonstrate context-aware perception, selectively attending to task-relevant features and integrating multi-modal inputs. These agents can interpret perceptual information in relation to goals and social context.
- Self-Aware Agents exhibit metacognitive awareness of perceptual limitations, enabling uncertainty estimation and active information seeking to resolve ambiguities. These agents can reason about what they do not perceive and adjust accordingly.

Despite these advances, significant challenges remain in developing perceptual systems that match human capabilities in understanding novel environments, recognizing unusual situations, and integrating information across modalities under resource constraints. These limitations are caused by three factors: first, perception models are trained on static datasets that fail to generalize to novel situations and environments due to distribution mismatch; second, lack of representations for rare or unusual situations like safety-critical scenarios; third, agents perceive data from multiple sensory sources and surroundings that process text, images, audio, etc. However, LLMs often misinterpret sensory data due to lack of grounding, leading to hallucinations or incorrect assumptions. They also struggle with unfamiliar inputs that were not seen during training.

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IV. AI AND MACHINE LEARNING APPROACHES FOR AGENTIC AI SYSTEMS

Artificial Intelligence (AI) and Machine Learning (ML) form the foundation of Agentic AI systems, enabling autonomous agents to perceive their environment, learn from experience, make decisions, and adapt to changing conditions. Unlike conventional AI systems that follow predefined rules, Agentic AI employs advanced learning approaches to achieve goal-oriented behavior, reasoning, and continuous improvement [18]. Various AI and ML techniques contribute to these capabilities by enhancing an agent's ability to understand complex environments, generalize across tasks, and execute actions effectively. Some techniques are presented below:

A. Reinforcement Learning Agents

Reinforcement Learning (RL) trains agents via trial-and-error interaction, updating policies to maximize cumulative rewards. Modern deep RL has shown impressive capabilities in dynamic domains (e.g., AlphaGo, autonomous navigation, robotics) [19]. RL agents embody adaptivity and goal-directedness, aligning with Agentic AI. However, they typically lack explicit internal representations of beliefs or intentions, instead focusing on optimization— a key distinction in debates about full-fledged agency.

B. Multi-Task Learning

In multi-task learning agents acquire the capabilities to perform several tasks at once, which expands their generalization abilities over multiple goals, tasks, and scenarios [20]. The problem is of utmost interest in designing agentic AI systems that are supposed to tackle multiple objectives in parallel.

C. Hierarchical Reinforcement Learning (Hrl)

HRL structures decision-making hierarchically, where high-level agents define sub-goals, and low-level agents execute them. This approach is effective for managing tasks with multiple levels of complexity.

D. Imitation Learning (IL)

IL plays a pivotal role in building agentic AI systems; see [21]. In IL agents learn behaviors 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.

E. Curriculum Learning

Structure tasks in increasing order of complexity so that an agent develops basic skills that can be built upon in new, more complex tasks [22]. Such a structure of progressively more complex tasks is fundamental in a multi-goal-oriented environment.

F. Multi-Modal Learning

which fuses information from multiple sources and types to better understand different situations, may assist in improving the versatility of Agentic AI systems in the operative context [23]. With visual, auditory, and other kinds of information, multimodal learning can be particularly effective for autonomous vehicles trying to function in complex situations [24].

V. LITERATURE REVIEW

This section provides a survey of prior work on a comparable subject and keywords relevant to it. Table III presents the comparative study of literature review.

H. Apuri and C. Yepuri (2026) concentrate on the architectural design, implementation strategies, and applications of systems centered on MAS, emphasizing decision intelligence, scalability, and flexibility as paramount. This study talks about the systems and how advanced machine learning and reinforcement learning are used in them. It also suggests a

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way to build the best autonomous workflow systems. The systems can make the economy more productive, and they add value to the complicated fields of business operations, health care, manufacturing, and logistics. The systems give users a lot of value by making them more effective and improving their decision-making systems [25].

Y. Ren et al. (2025) Agentic AI contributes to expanding AI's capabilities in information processing, environmental perception, and autonomous decision-making, opening new avenues for smart manufacturing. To address this gap, this study systematically reviews the evolution of AI and AI agent technologies, examines the core concepts and technological advancements of LLM-Agents, MLLM-Agents, and Agentic AI, and explores their potential applications in and integration into manufacturing, along with the potential challenges they may face [26].

I. Okpala et al. (2025) explore the architecture of the agentic crew, which consists of a judge agent along with role-specific agents to facilitate comprehensive model evaluations, ensuring adherence to regulatory standards and enhancing the conceptual soundness of the evaluated procedure. The application of agentic systems in MRM is illustrated through case studies in fraud detection and portfolio credit risk assessment. Our findings suggest that adopting human-centered agentic systems can lead to more informed decision-making processes, identifying whether the model development followed an established procedure, assessing reproducibility, bias and fairness, and monitoring changes in behavior when unknown inputs are introduced [27].

C.-M. Yang et al. (2025) synthesize recent research to demonstrate how Agentic AI strengthens anomaly detection, autonomously executes defensive strategies, and supports real-time mitigation of cyber threats. Beyond security, the framework optimizes power distribution and coordinates charging schedules, improving operational reliability and efficiency. The analysis also addresses implementation challenges, including computational demands, interoperability, and the need for standardized protocols. Overall, the findings highlight Agentic AI's potential to establish a secure, resilient, and adaptive foundation for EV-integrated microgrids, contributing to the development of a more sustainable and reliable decentralized energy ecosystem [28].

S. Arora and J. Hastings (2025) introduce MAAIS, an agentic security framework, and the agentic AI CIAA (Confidentiality, Integrity, Availability, and Accountability) concept. MAAIS integrates multiple defense layers to maintain CIAA across the AI lifecycle. Framework validation is conducted by mapping with the established MITRE ATLAS (Adversarial Threat Landscape for Artificial-Intelligence Systems) AI tactics. The study contributes a structured, standardized, and framework-based approach for the secure deployment and governance of agentic AI in enterprise environments. This framework is intended for enterprise CISOs, security, AI platform, and engineering teams and offers a detailed step-by-step approach to securing agentic AI workloads [29].

S. Panda and A. Padhy (2025) widespread adoption of distributed applications-including the Internet, mobile networks, peer-to-peer and volunteer computing, and sensor networks-has increased interest in empowering devices to operate with greater autonomy. A distributed system comprises multiple hosts that cooperate to appear as a single system, offering extensive resources, high availability, and scalability. Multi-agent systems represent another form of distributed systems comprising autonomous, interactive agents that collaborate or compete to solve complex problems exceeding individual capabilities. Agentic AI augments multi-agent systems with reasoning abilities that enable the selection and pursuit of high-level human-defined targets comprehensible by the agents. While some agents receive training for machine learning in multi-agent reinforcement learning settings, such training yields only low-level skills [30]

Table 3: Comparison of Recent Studies on Building Agentic AI Systems

Reference	Approach	Advantages	Challenges	Recommendations
H. Apuri and C. Yepuri (2026	Multi-Agent System (MAS)-based autonomous workflow framework using ML and Reinforcement Learning.	Provides scalability, flexibility, decision intelligence, and workflow automation.	Agent coordination, resource management, and deployment complexity.	Develop robust coordination protocols and optimize resource allocation strategies.

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Y. Ren et al. (2025)	Systematic review of LLM-Agents, MLLM-Agents, and Agentic AI for smart manufacturing.	Enhances autonomous decision-making, environmental perception, and manufacturing intelligence.	Unclear capability boundaries, integration complexity, and lack of standardized implementation frameworks.	Develop standardized architectures and evaluation metrics for manufacturing applications.
I. Okpala et al. (2025)	Human-in-the-loop agentic crew for Machine Learning Model Risk Management (MRM).	Improves regulatory compliance, fairness assessment, reproducibility, and model monitoring.	Dependence on expert oversight and increased system complexity.	Strengthen collaboration mechanisms between human experts and autonomous agents.
C.-M. Yang et al.(2025)	Agentic AI framework for cybersecurity in EV-integrated microgrids.	Enables real-time threat detection, autonomous response, and optimized power management.	High computational requirements, interoperability issues, and lack of standard protocols.	Establish industry standards and lightweight security mechanisms for large-scale deployment.
S. Arora and J. Hastings (2025)	MAAIS lifecycle-aware security framework for Agentic AI systems.	Ensures Confidentiality, Integrity, Availability, and Accountability (CIAA) throughout the AI lifecycle.	Complex implementation and evolving AI security threats.	Creates unified governance policies and continuous security monitoring mechanisms.
S. Panda and A. Padhy(2025)	Agentic AI-enhanced Multi-Agent Systems in distributed environments.	Supports autonomous reasoning, collaboration, and high-level goal achievement.	Limited high-level skill learning and coordination challenges among agents.	Integrate advanced reasoning models and adaptive learning techniques to improve agent capabilities.

Research Gap: Despite recent advancements in Agentic AI, several challenges remain unresolved. Existing studies lack standardized architectures and evaluation frameworks, making it difficult to compare and validate different agentic systems. Most research focuses on domain-specific applications, while the scalability and generalizability of Agentic AI across diverse environments remain underexplored. Additionally, issues related to explainability, security, governance, and human–AI collaboration require further investigation. There is also limited research on developing trustworthy and ethical agentic systems capable of long-term autonomous decision-making in dynamic real-world scenarios.

VI. CONCLUSION

The rapid emergence of Agentic AI is reshaping the landscape of intelligent systems by extending artificial intelligence beyond passive prediction and content generation toward autonomous reasoning, planning, and action execution. Through the integration of advanced architectures, adaptive learning mechanisms, and collaborative agent frameworks, Agentic AI enables systems to operate effectively in complex and dynamic environments. This survey examined the foundational concepts, architectural designs, learning paradigms, and diverse application areas that collectively define the current Agentic AI ecosystem. The reviewed studies demonstrate substantial progress in developing autonomous and goal-driven systems capable of supporting decision-making across domains such as manufacturing, cybersecurity, healthcare, and enterprise automation. However, the analysis also reveals persistent challenges related to system reliability, transparency, coordination among multiple agents, security, and governance. Addressing these challenges is essential for realizing the full potential of Agentic AI and ensuring its responsible adoption. As research and industrial adoption continue to

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accelerate, Agentic AI is expected to become a fundamental component of next-generation intelligent systems, driving greater autonomy, efficiency, and adaptability across a wide range of real-world applications.

Future research should focus on developing secure, transparent, and trustworthy agentic systems while improving human–AI collaboration and standardization. As technology continues to evolve, Agentic AI is expected to play a crucial role in building next-generation intelligent systems capable of addressing complex real-world challenges effectively and autonomously.

REFERENCES

[1] S. Khapre et al., "Agentic AI systems: A systematic survey of multi-agent architectures, cognitive foundations, interaction, explainability, security, and performance evaluation," Neurocomputing, vol. 696, p. 134049, Oct. 2026, doi: 10.1016/j.neucom.2026.134049.

[2] N. Sayyad, H. Dave, M. Kathane, and R. Patel, "Agentic AI Systems: A Review of Architectures, Autonomy, and Ethical Implications," Int. J. Environ. Sci., vol. 10, no. 4, pp. 3668–3683, Oct. 2025, doi: 10.64252/xgfrhd85.

[3] R. Dandigam, R. T. Thutari, and T. Vaidya, "LLM-Augmented Agentic Consensus Swarms for Autonomous Edge Security," in 2026 14th International Symposium on Digital Forensics and Security (ISDFS), IEEE, Mar. 2026, pp. 1–8. doi: 10.1109/ISDFS69419.2026.11459110.

[4] N. Bhandarwar, "Integrating Generative AI and Model Context Protocol (MCP) with Applied Machine Learning for Advanced Agentic AI Systems," Int. J. Comput. Trends Technol., vol. 73, no. 8, pp. 7–14, August, Aug. 2025, doi: 10.14445/22312803/IJCTT-V73I8P102.

[5] B. P. Singh, "Securing the Boundary: Trust Context Separation in Privileged AI Agent Systems," Comput. Fraud Secur., vol. 2026, no. 1, pp. 998–1009, 2026, doi: 10.5281/zenodo.19487302.

[6] I. Adabara, B. Olaniyi Sadiq, A. Nuhu Shuaibu, Y. Ibrahim Danjuma, and V. Maninti, "Trustworthy agentic AI systems: a cross-layer review of architectures, threat models, and governance strategies for real-world deployment," F1000Research, vol. 14, p. 905, Sep. 2025, doi: 10.12688/f1000research.169927.1.

[7] A. Bandi, B. Kongari, R. Naguru, S. Pasnoor, and S. V. Vilipala, "The Rise of Agentic AI: A Review of Definitions, Frameworks, Architectures, Applications, Evaluation Metrics, and Challenges," Futur. Internet, vol. 17, no. 9, p. 404, Sep. 2025, doi: 10.3390/fi17090404.

[8] N. Brandon et al., "Simulating exposure-related behaviors using agent-based models embedded with needs-based artificial intelligence," J. Expo. Sci. Environ. Epidemiol., vol. 30, no. 1, pp. 184–193, Jan. 2020, doi: 10.1038/s41370-018-0052-y.

[9] C. Chawla, S. Chatterjee, S. S. Gadadinni, P. Verma, and S. Banerjee, "Agentic AI: The building blocks of sophisticated AI business applications," J. AI, Robot. Work. Autom., vol. 3, no. 3, p. 196, Sep. 2024, doi: 10.69554/XEHZ1946.

[10] A. K. Pati, "Agentic AI: A Comprehensive Survey of Technologies, Applications, and Societal Implications," IEEE Access, vol. 13, no. September, pp. 151824–151837, 2025, doi: 10.1109/ACCESS.2025.3585609.

[11] S. Yao et al., "React: Synergizing Reasoning And Acting In Language Models," in 11th International Conference on Learning Representations, ICLR 2023, 2023. doi: 10.48550/arXiv.2210.03629.

[12] V. Garg, "Designing the Mind: How Agentic Frameworks Are Shaping the Future of AI Behavior," J. Comput. Sci. Technol. Stud., vol. 7, no. 5, pp. 182–193, May 2025, doi: 10.32996/jcsts.2025.7.5.24.

[13] M. Kumar and R. Jaggavarapu, "The Evolution of Agentic AI: Architecture and Workflows for Autonomous Systems," SARC Publ., vol. 5, no. 7, pp. 418–427, 2025, doi: 10.5281/zenodo.15876888.

[14] S. Hosseini and H. Seilani, "The role of agentic AI in shaping a smart future: A systematic review," Array, vol. 26, p. 100399, Jul. 2025, doi: 10.1016/j.array.2025.100399.

[15] J. Huggett, "Algorithmic Agency and Autonomy in Archaeological Practice," Open Archaeol., vol. 7, no. 1, pp. 417–434, Jun. 2021, doi: 10.1515/opar-2020-0136.

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[16] N. Kolli, J. W. Sajja, and A. Nerella, "Building Secure AI Agents for Autonomous Data Access in Compliance/Regulatory-Critical Environments," Comput. Fraud Secur., vol. 2024, no. 9, pp. 363–373, Sep. 2024, doi: 10.52710/cfs.746.
[17] U. Nisa, M. Shirazi, M. A. Saip, and M. S. M. Pozi, "Agentic AI: The age of reasoning—A review," J. Autom. Intell., vol. 5, no. 1, pp. 69–89, Mar. 2026, doi: 10.1016/j.jai.2025.08.003.
[18] N. Choppa and N. Kolli, "Contextual Frameworks for Agentic AI: Engineering Adaptive Memory and Retrieval Mechanisms," Comput. Fraud Secur, vol. 11, no. 12, 2024.
[19] A. Nagabandi, K. Konolige, S. Levine, and V. Kumar, "Deep Dynamics Models for Learning Dexterous Manipulation," in Proceedings of Machine Learning Research, 2019. doi: 10.48550/arXiv.1909.11652.
[20] R. V. S. S. B. R, A. M, S. Sharhrah, K. Keerthana, and S. Senthil, "A Personalized Federated Multi-Task Learning Framework for Multi-Modal COVID-19 Diagnosis at the Edge," in 2025 Third International Conference on Networks, Multimedia and Information Technology (NMITCON), IEEE, Aug. 2025, pp. 1–6. doi: 10.1109/NMITCON65824.2025.11188318.
[21] A. Pozzi and D. Toti, "Imitation Learning for Agnostic Battery Charging: A DAGGER-Based Approach," IEEE Access, vol. 11, pp. 115190–115203, 2023, doi: 10.1109/ACCESS.2023.3325194.
[22] X. Wang, Y. Chen, and W. Zhu, "A Survey on Curriculum Learning," IEEE Trans. Pattern Anal. Mach. Intell., vol. 44, no. 9, pp. 4555–4576, 2021, doi: 10.1109/TPAMI.2021.3069908.
[23] Y. Huang, C. Du, Z. Xue, X. Chen, H. Zhao, and L. Huang, "What Makes Multi-modal Learning Better than Single (Provably)," in Advances in Neural Information Processing Systems, 2021. doi: 10.48550/arXiv.2106.04538.
[24] D. B. Acharya, K. Kuppan, and B. Divya, "Agentic AI: Autonomous Intelligence for Complex Goals—A Comprehensive Survey," IEEE Access, vol. 13, pp. 18912–18936, 2025, doi: 10.1109/ACCESS.2025.3532853.
[25] H. Apuri and C. Yepuri, "Design of Multi-Agent Autonomous Workflow Systems using Agentic AI Frameworks," in 2026 International Conference on AI-Driven Smart Systems and Ubiquitous Computing (ICAUC), IEEE, Jan. 2026, pp. 1731–1737. doi: 10.1109/ICAUC68182.2026.11441280.
[26] Y. Ren, Y. Liu, T. Ji, and X. Xu, "AI Agents and Agentic AI–navigating a plethora of concepts for future manufacturing," J. Manuf. Syst., vol. 83, pp. 126–133, Dec. 2025, doi: 10.1016/j.jmsy.2025.08.017.
[27] I. Okpala, A. Golgoon, and A. R. K. Discover, "Model Risk Management in Finance: The Role of Agentic Systems in Risk Mitigation," in 2025 IEEE International Conference on Agentic AI (ICA), IEEE, Dec. 2025, pp. 1–6. doi: 10.1109/ICA67499.2025.00010.
[28] C.-M. Yang, M. Elsisi, and C.-L. Su, "Agentic AI for Enhancing Cyber-Resilience in EV Charging Microgrids," in 2025 26th International Middle East Power Systems Conference (MEPCON), IEEE, Dec. 2025, pp. 1–6. doi: 10.1109/MEPCON66918.2026.11360231.
[29] S. Arora and J. Hastings, "Securing Agentic AI Systems - A Multilayer Security Framework," in 2025 5th International Conference on Robotics, Automation, and Artificial Intelligence (RAAI), IEEE, Dec. 2025, pp. 509–514. doi: 10.1109/RAAI67517.2025.11423374.
[30] S. Panda and A. Padhy, "Agentic AI in Distributed Systems: Toward Autonomous, Goal-Oriented Decision-Making in Multi-Agent Environments," in 2025 5th International Conference on Mobile Networks and Wireless Communications (ICMNWC), IEEE, Dec. 2025, pp. 1–6. doi: 10.1109/ICMNWC66779.2025.11354453.