

# The Evolution of Generative and Agentic AI: From Rule-Based Systems to Autonomous Intelligence

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## Annotation

The rapid evolution of Artificial Intelligence (AI) has transitioned from rule-based systems to advanced generative and agentic models capable of autonomous decision-making and reasoning. Early AI frameworks relied heavily on symbolic logic and deterministic rules, offering limited adaptability and contextual understanding. With the advent of Machine Learning (ML) and Deep Learning (DL), AI systems gained the ability to learn from data and improve performance autonomously. The emergence of Generative AI (GenAI), powered by Large Language Models (LLMs) such as GPT, BERT, and Gemini, marked a paradigm shift by enabling contextual creativity, natural language understanding, and multimodal reasoning. Meanwhile, Agentic AI introduces a new dimension — systems capable of goal-driven autonomy, memory-based reasoning, and adaptive interaction with environments and users. This review explores the historical progression of AI technologies, from rule-based inference engines to generative and agentic intelligence, analyzing their architectural evolution, learning mechanisms, ethical challenges, and real-world applications. The paper also discusses the integration of Retrieval-Augmented Generation (RAG), MCP servers, and data-driven reinforcement models as enablers of scalable autonomous intelligence. Finally, future research directions emphasize hybrid intelligence frameworks, human-AI collaboration, and explainable autonomy for safe and responsible AI deployment.

**Keywords:** Artificial Intelligence, Large Language Models, Generative AI (GenAI), Retrieval-Augmented Generation, Autonomous Intelligence.



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## 1. Introduction

Artificial Intelligence (AI) has undergone a remarkable transformation since its inception [1]. Early AI systems relied on rule-based frameworks, which used symbolic logic and deterministic rules to mimic human reasoning [2]. While effective for simple decision-making, these systems suffered from limited adaptability, lack of context-awareness, and an inability to learn from data. The emergence of Machine Learning (ML) and Deep Learning (DL) brought a paradigm shift, enabling AI systems to learn autonomously from vast datasets and improve performance over time [3-4].

The advent of Generative AI (GenAI), particularly Large Language Models (LLMs) such as GPT, BERT, and Gemini, marked a new era in AI research [5]. These models demonstrate advanced natural language understanding, creativity, and multimodal reasoning capabilities, making them suitable for applications ranging from content generation to knowledge synthesis [6]. Parallely, Agentic AI introduces systems capable of autonomous decision-making, memory-based reasoning, and adaptive interaction with dynamic environments. Together, these developments highlight a trajectory from deterministic AI to autonomous, goal-directed intelligence, reshaping industries, research, and societal applications [7-8].

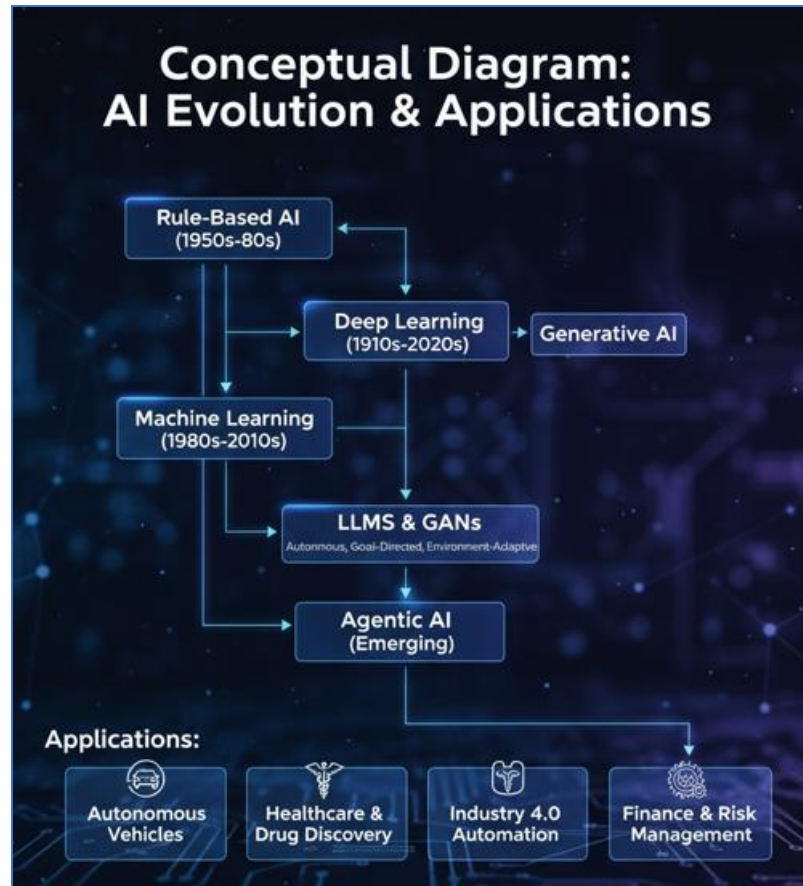


Fig. 1: Conceptual diagram for AI evolution & Applications

This paper presents a comprehensive review of AI’s evolution, examining historical frameworks, architectural advances, learning mechanisms, ethical considerations, and real-world implementations. Additionally, we explore enabling technologies such as Retrieval-Augmented Generation (RAG) [9-12], MCP servers, and reinforcement-based learning as cornerstones for scalable, autonomous intelligence.

**Table 1: Overview of IoT Device Design Components**

Component	Description	Examples / Technologies	Key Considerations
Microcontroller / Processor	The core computing unit that controls device operations	Arduino, Raspberry Pi, ESP32, STM32	Power consumption, processing speed, cost
Sensors	Capture environmental or system data	Temperature, Humidity, Motion, Light, Gas	Accuracy, response time, calibration
Actuators	Devices that perform physical actions based on controller commands	Motors, Relays, LEDs, Servos	Torque, voltage requirements, response time
Connectivity	Enable communication	Wi-Fi, Bluetooth,	Range, power usage,

Modules	between devices or to the cloud	Zigbee, LoRa, 5G, NB-IoT	data rate, protocol
Power Supply / Management	Provides energy to the device and manages consumption	Batteries, Solar Panels, Voltage Regulators	Battery life, efficiency, sustainability
Memory & Storage	Store firmware, sensor data, and temporary computations	Flash, EEPROM, SD Cards	Size, read/write speed, endurance
Embedded Software / Firmware	Controls device operation, connectivity, and data processing	C/C++, Python, RTOS (FreeRTOS), Embedded Linux	Efficiency, real-time response, security
Cloud & IoT Platform	Collects, stores, and analyzes IoT data remotely	AWS IoT, Azure IoT Hub, Google Cloud IoT	Scalability, latency, security
Security Layer	Protects device and network from unauthorized access and cyber attacks	TLS/SSL, VPN, Authentication Protocols	Encryption strength, key management, updates
Application Layer	Interface for end-users to monitor and control IoT devices	Mobile apps, Web dashboards, Voice Assistants	User-friendliness, responsiveness, customization

## 2. Historical Overview of AI

### 2.1 Rule-Based Systems

Rule-based systems, also known as expert systems, represent the earliest AI implementations. They rely on explicit if-then logic to perform reasoning tasks. Although effective in domains like medical diagnosis and industrial control, these systems are inherently static and cannot adapt to unseen scenarios without manual intervention [5, 13].

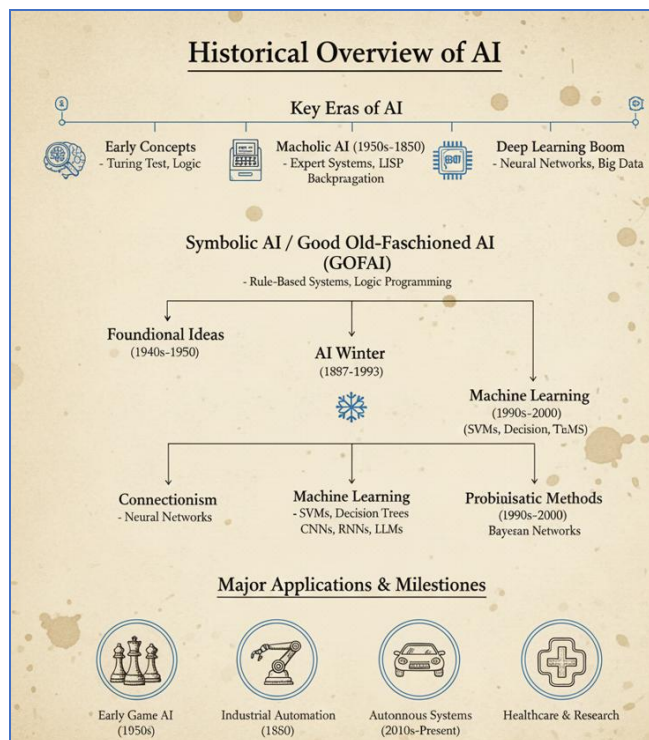


Fig.2: Historical overview of AI

### 2.2 Emergence of Machine Learning

Machine Learning shifted AI from rigid rules to data-driven learning. Supervised, unsupervised, and reinforcement learning techniques allowed models to extract patterns from data and make probabilistic predictions [6, 14-15]. This marked the beginning of AI's self-improvement

capabilities, extending its application to computer vision, speech recognition, and predictive analytics.

### 2.3 Deep Learning

The rise of Deep Learning further enhanced AI’s ability to model complex, non-linear relationships using neural networks. Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transformers enabled AI to handle high-dimensional data, leading to breakthroughs in image, text, and speech processing [16].

### 3. Generative AI and Large Language Models

Generative AI (GenAI) focuses on creating new content from learned data patterns. Key architectures include:

- Generative Adversarial Networks (GANs): Produce realistic images, videos, or audio by training a generator and a discriminator in competition.
- Large Language Models (LLMs): Transformers like GPT and BERT understand and generate human-like text with high contextual accuracy.

GenAI models can perform multimodal reasoning, handle complex queries, and support applications such as code generation, summarization, and conversational agents. However, challenges such as bias, hallucinations, and high computational demands remain.

### 4. Agentic AI

Agentic AI represents the next frontier, combining autonomy, goal-directed behavior, and environmental interaction. Unlike traditional ML or GenAI, agentic systems can:

- Set and pursue objectives autonomously
- Maintain memory of past experiences
- Learn from dynamic environments and human interactions

Applications include autonomous robotics, adaptive AI assistants, smart decision systems, and intelligent IoT frameworks. Integration with RAG enhances decision-making by allowing real-time knowledge retrieval, while MCP servers provide the necessary computational scalability [12, 17].

### 5. Enabling Technologies

**Table 2: Technology verses role in AI Evolution**

Technology	Role in AI Evolution
RAG (Retrieval-Augmented Generation)	Enhances LLM outputs with real-time information, reducing hallucinations.
MCP Servers	Supports large-scale AI model training, distributed processing, and high-performance workloads.
Reinforcement Learning	Enables adaptive, reward-based learning for autonomous agentic systems.
Data Science & Big Data	Provides structured and unstructured datasets essential for training advanced AI models.

**Table 3: Generative AI vs Agentic AI vs Rule-Based Systems**

Feature	Rule-Based Systems	Generative AI (LLMs/GenAI)	Agentic AI
Decision-making	Deterministic, based on predefined rules	Probabilistic, data-driven	Autonomous, goal-directed
Adaptability	Low	Medium	High

<i>Learning</i>	No	Supervised/unsupervised training	Continuous learning with environment interaction
<i>Data Requirement</i>	Minimal	Large datasets	Very large datasets and environment feedback
<i>Applications</i>	Expert systems, legacy automation	Text/image generation, summarization, coding	Robotics, autonomous agents, AI assistants
<i>Complexity</i>	Low	High	Very high
<i>Error Handling</i>	Limited	Can hallucinate	Adaptive, can self-correct

## 6. Literature Review

**Table 4: Literature Review Applications of Generative and Agentic AI**

Sector	Technology	Key Applications	Key References
Autonomous Vehicles	GenAI & Agentic AI	<ul style="list-style-type: none"> <li>- Perception &amp; Decision-Making: Integration of sensor data (e.g., LIDAR, cameras) for real-time environment understanding.</li> <li>- Navigation: Autonomous path planning and obstacle avoidance.</li> <li>- Safety Systems: Predictive analytics for accident prevention.</li> </ul>	<ul style="list-style-type: none"> <li>- Jabbour, J., &amp; Reddi, V. J. (2024) [1]. <i>Generative AI Agents in Autonomous Machines: A Safety Perspective</i>. arXiv. <a href="#">arXiv</a></li> <li>- Nascimento, A. M., et al. (2019) [4]. <i>A Systematic Literature Review about the impact of Artificial Intelligence on Autonomous Vehicle Safety</i>. arXiv. <a href="#">arXiv</a></li> </ul>
Healthcare	GenAI & Agentic AI	<ul style="list-style-type: none"> <li>- Medical Imaging: Automated analysis and interpretation of radiological images.</li> <li>- Drug Discovery: Generative models for novel compound generation.</li> <li>- Personalized Medicine: Tailored treatment plans based on patient data.</li> <li>- Clinical Decision Support: AI-driven recommendations for diagnosis and treatment.</li> </ul>	<ul style="list-style-type: none"> <li>- Karunanayake, N. (2025) [5]. <i>Next-generation agentic AI for transforming healthcare</i>. ScienceDirect. <a href="#">ScienceDirect</a></li> <li>- Chalasani, S. H., et al. (2023) [6]. <i>Artificial intelligence in the field of pharmacy practice: A literature review</i>. Exploratory Research in Clinical and Social Pharmacy. <a href="#">Wikipedia</a></li> </ul>
Industry 4.0	GenAI & Agentic AI	<ul style="list-style-type: none"> <li>- Predictive Maintenance: Forecasting equipment failures using AI models.</li> <li>- Supply Chain Optimization: Enhancing logistics and inventory management.</li> <li>- Quality Control: Automated inspection and defect detection.</li> <li>- Process Automation: Streamlining manufacturing workflows.</li> </ul>	<ul style="list-style-type: none"> <li>- Olujimi, P. A. (2025) [5]. <i>Agentic AI Frameworks in SMMES: A Systematic Literature Review</i>. Preprints. <a href="#">Preprints</a></li> <li>- MDPI. (2025). <i>Design of a Smart Factory Based on Cyber-Physical Systems and Internet of Things</i>. MDPI. <a href="#">Wikipedia</a></li> </ul>
Finance	GenAI & Agentic AI	<ul style="list-style-type: none"> <li>- Risk Assessment: Evaluating financial risks using AI models.</li> <li>- Fraud Detection: Identifying fraudulent activities through pattern recognition.</li> <li>- Algorithmic Trading: Developing trading strategies</li> </ul>	<ul style="list-style-type: none"> <li>- Joshi, S. (2025) [8]. <i>A Literature Review of Gen AI Agents in Financial Applications: Models and Implementations</i>. SSRN. <a href="#">ResearchGate</a></li> <li>- Investopedia. (2023). <i>Generative AI and Its Economic Impact: What You Need to Know</i>. Investopedia</li> </ul>

		using AI - Customer Support: AI-powered chatbots and virtual assistants.	
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**Table 5: Evolution of AI: Comparative Summary [1-5]**

AI Generation	Era / Year	Core Approach	Learning / Adaptation	Key Applications	Limitations
<i>Rule-Based Systems</i>	1950s – 1980s	Symbolic logic, deterministic rules	None; manual updates only	Expert systems, industrial control	Low adaptability, cannot handle uncertainty
<i>Machine Learning</i>	1980s – 2010s	Statistical models, supervised/unsupervised learning	Learns from data	Predictive modeling, computer vision, speech recognition	Requires large labeled datasets, limited contextual reasoning
<i>Deep Learning</i>	2010s – 2020s	Neural networks, CNN, RNN, Transformers	Learns hierarchical patterns	Image recognition, NLP, speech synthesis	High computational cost, black-box nature
<i>Generative AI (GenAI)</i>	2020s – present	LLMs, GANs, diffusion models	Data-driven content generation	Text generation, image synthesis, code generation, summarization	Hallucination, bias, compute-intensive
<i>Agentic AI</i>	Emerging (2023 onwards)	Goal-driven autonomous agents	Continuous learning from environment & feedback	Autonomous vehicles, robotics, adaptive AI assistants	Complexity, safety, explainability challenges

**Table 6: Applications & Case Study Summary**

Application Domain	AI Model	Functions / Capabilities	Enabling Technologies	Key Insights / Findings
<i>Autonomous Vehicles</i>	Agentic AI	Perception, navigation, decision-making	RAG, LLMs, Reinforcement Learning, Sensor Fusion	Achieves high autonomy levels (L4/L5) with real-time adaptive learning
<i>Healthcare</i>	GenAI + Agentic AI	Diagnosis, personalized treatment, drug discovery	RAG, Big Data, LLMs, GenAI	Improves diagnostic accuracy and accelerates drug design
<i>Industry 4.0</i>	Agentic AI + GenAI	Predictive maintenance, process optimization, quality control	MCP Servers, IoT, ML, Data Mining	Reduces downtime and optimizes production workflows
<i>Finance</i>	GenAI + Agentic AI	Risk assessment, fraud detection, algorithmic trading	RAG, LLMs, Big Data, Reinforcement Learning	Enhances real-time decision-making and fraud prevention

**Table 7: Insights from Literature**

Aspect	Observations
Learning Mechanisms	Evolution from static rules → supervised ML → deep learning → GenAI → agentic autonomous learning

Adaptability	Rule-based AI: low; GenAI: medium; Agentic AI: high, capable of goal-driven adaptation
Computational Requirements	Increasing from simple rule engines to high-performance MCP servers for agentic AI
Ethical & Safety Considerations	Agentic AI and GenAI require explainable, accountable, and bias-mitigated systems
Impact Across Sectors	Significant improvements in autonomous navigation, healthcare diagnostics, industrial automation, and financial decision-making

## 7. Applications and Case Studies

### 7.1. Autonomous Vehicles

Autonomous vehicles (AVs) represent one of the most complex real-world applications of AI, combining perception, decision-making, navigation, and interaction with dynamic environments. Traditional ML algorithms in AVs focused on object detection, lane recognition, and basic decision-making [18-19]

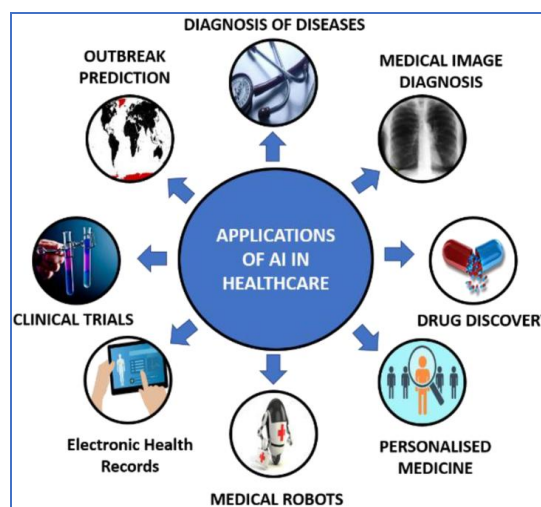
Agentic AI enables vehicles to operate autonomously, dynamically adapting to traffic conditions, pedestrian movements, and unforeseen scenarios. Key components include:

- Perception: Lidar, radar, and camera sensor fusion for environment understanding.
- Decision-Making: Goal-driven planning using reinforcement learning and agentic strategies.
- Navigation: Real-time path planning and trajectory optimization.
- Enhancements via RAG and LLMs:
- RAG-enabled LLMs can provide AVs with contextual knowledge, e.g., interpreting traffic regulations or road updates.
- Agentic models allow the system to learn from experience, improving driving strategies over time.

Companies like Tesla, Waymo, and Cruise leverage deep neural networks, reinforcement learning, and agentic AI frameworks for Level 4–5 autonomous driving. These vehicles continuously optimize performance based on real-time feedback from sensors and external knowledge bases.

### 7.2. Healthcare

Healthcare applications of AI have evolved from diagnostic support to personalized treatment planning and drug discovery. GenAI and LLMs are increasingly used to process unstructured medical data, clinical notes, and biomedical literature [12, 14, 15, 18-22].



**Fig.3: Applications of AI in Healthcare**

- **Medical Diagnosis:** LLMs analyse patient history, lab reports, and medical literature to assist clinicians in identifying diseases.
- **Personalized Treatment:** Agentic AI models can propose treatment strategies based on patient-specific data, genetic markers, and historical outcomes [21, 24].
- **Drug Discovery:** Generative models create novel molecular structures and predict drug-target interactions, accelerating R&D timelines.
- **Retrieval-Augmented Generation** ensures that AI systems access up-to-date medical knowledge and guidelines in real time, improving diagnostic accuracy.

IBM Watson Health has leveraged AI and GenAI for oncology treatment recommendations, while DeepMind's AlphaFold uses ML and AI to predict protein structures for drug discovery.

### **7.3. Industry 4.0**

Industry 4.0 emphasizes automation, real-time analytics, and intelligent control systems in manufacturing and industrial processes. AI-driven predictive maintenance, process optimization, and quality assurance are central to this transformation.

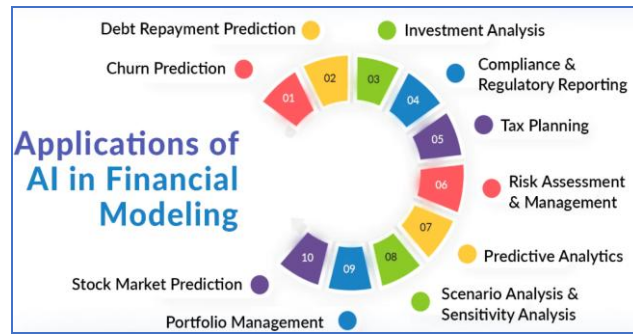
- **Predictive Maintenance:** Agentic AI monitors equipment performance, detects anomalies, and autonomously schedules maintenance to prevent failures.
- **Automated Control Systems:** AI systems optimize production schedules, energy consumption, and supply chain operations.
- **Data-Driven Insights:** GenAI models analyze historical and sensor data to generate actionable insights for operational efficiency.
- Large-scale AI workloads are executed on MCP servers, enabling real-time data processing and decision-making across multiple industrial units.

Siemens and General Electric use AI-driven predictive maintenance frameworks, combining ML, IoT sensor data, and agentic AI models to reduce downtime and enhance efficiency.

### **7.4. Finance**

The financial sector is increasingly adopting AI for risk management, fraud detection, and automated trading, leveraging both predictive models and generative intelligence.

- **Risk Assessment:** ML models analyze market trends, customer profiles, and economic indicators to evaluate risks.
- **Fraud Detection:** Agentic AI detects unusual patterns in transactions and autonomously triggers alerts.
- **Automated Trading:** AI-driven trading bots use reinforcement learning to adapt strategies based on market behavior and historical data [21, 25].
- **RAG and LLM Applications:**
- LLMs assist in financial document analysis, sentiment extraction, and regulatory compliance [26].
- RAG enables AI to retrieve real-time market news or financial reports, improving decision-making accuracy.



**Fig. 4: Applications of AI in Financial modelling**

**Table 8: Summary Table: Applications and AI Integration**

Application	AI Type	Key Functions	Supporting Technologies
<i>Autonomous Vehicles</i>	Agentic AI	Perception, decision-making, navigation	RAG, LLMs, Reinforcement Learning, Sensor Fusion
<i>Healthcare</i>	GenAI + Agentic AI	Diagnosis, personalized treatment, drug discovery	RAG, LLMs, Big Data Analytics, GenAI models
<i>Industry 4.0</i>	GenAI + Agentic AI	Predictive maintenance, process optimization	MCP Servers, IoT, Data Mining, ML
<i>Finance</i>	Agentic AI + GenAI	Risk assessment, fraud detection, automated trading	RAG, LLMs, Reinforcement Learning, Big Data

**Conclusion**

The evolution of Artificial Intelligence has progressed through distinct phases — from deterministic rule-based systems to adaptive machine learning and deep learning models, culminating in today’s Generative and Agentic AI paradigms. Each generation has enhanced autonomy, adaptability, and contextual understanding. Generative AI (GenAI), powered by Large Language Models (LLMs) such as GPT, BERT, and Gemini, revolutionized natural language understanding, multimodal creativity, and automated knowledge generation. In contrast, Agentic AI represents the next frontier — enabling goal-directed, memory-driven, and self-adaptive intelligence that interacts dynamically with both human users and real-world environments.

From the literature and applications reviewed, it is evident that RAG (Retrieval-Augmented Generation), MCP servers, and Reinforcement Learning frameworks act as critical enablers for scalable, context-aware, and high-performance AI ecosystems. These technologies bridge the gap between static data-driven systems and dynamic, reasoning-capable agents. The sectoral applications analyzed — autonomous vehicles, healthcare, Industry 4.0, and finance — demonstrate how GenAI and Agentic AI are transforming automation, decision-making, and human-machine collaboration.

In autonomous systems, Agentic AI enhances situational awareness and navigation, leading to near Level 5 autonomy. In healthcare, GenAI accelerates diagnostics and drug discovery while personalizing treatment. Industrial automation benefits from predictive maintenance and smart optimization, and finance witnesses improved fraud detection and real-time trading analytics through hybrid AI frameworks.

However, challenges persist bias, hallucinations, explainability, computational cost, and ethical governance remain pressing concerns. As AI systems gain autonomy, the need for transparency, accountability, and explainable decision-making becomes paramount.

Future research should focus on developing hybrid intelligence architectures that integrate symbolic reasoning, generative creativity, and agentic autonomy. Emphasis should be placed on

human-AI collaboration, energy-efficient computation, and responsible deployment to ensure that AI evolves as a reliable, transparent, and sustainable force for innovation across all sectors.

### References:

1. J. Jabbour and V. J. Reddi, "Generative AI Agents in Autonomous Machines: A Safety Perspective," *arXiv preprint*, arXiv:2403.06752, 2024.
2. B. A. Kumar, N. K. Misra, N. Pathak, S. Ahmadpour, M. Krishnamoorthy, and M. Patidar, "Hybrid CMNV2: DeepFake Faces Classification and Recognition using Deep Learning Methods," *Results in Engineering*, vol. 107513, 2025.
3. M. Patidar, P. Bhanodia, S. Patel, D. Mishra, R. Shukla, D. K. Sharma, et al., "Design and Exploration of Data-Handling Quantum-Computational Computer Circuits for the Implementation," in *Beyond Artificial Intelligence: Select Proceedings of the International Conference*, 2025.
4. A. M. Nascimento, M. A. Neto, and S. R. da Silva, "A Systematic Literature Review about the Impact of Artificial Intelligence on Autonomous Vehicle Safety," *arXiv preprint*, arXiv:1905.01998, 2019.
5. N. Karunanayake, "Next-Generation Agentic AI for Transforming Healthcare," *ScienceDirect*, 2025.
6. S. H. Chalasani, M. Kumar, and P. Sharma, "Artificial Intelligence in the Field of Pharmacy Practice: A Literature Review," *Exploratory Research in Clinical and Social Pharmacy*, 2023.
7. P. A. Olujimi, "Agentic AI Frameworks in SMMEs: A Systematic Literature Review," *Preprints*, 2025.
8. S. Joshi, "A Literature Review of Generative AI Agents in Financial Applications: Models and Implementations," *SSRN Electronic Journal*, 2025.
9. D. Desai, H. Baria, A. Chauhan, G. Yadav, M. Patidar, M. Mahale, A. Dave, et al., "Website Vulnerability Scanning Extension," *IET Conference Proceedings CP920*, vol. 2025(7), pp. 130–136, 2025.
10. M. Patidar, M. A. Jain, K. Patidar, S. K. Shukla, A. H. Majeed, N. Gupta, and N. Patidar, "An Ultra-Dense and Cost-Efficient Coplanar RAM Cell Design in Quantum-Dot Cellular Automata Technology," *The Journal of Supercomputing*, vol. 80, no. 5, pp. 6989–7027, 2024.
11. *Investopedia*, "Generative AI and Its Economic Impact: What You Need to Know," 2023. [Online]. Available: <https://www.investopedia.com>
12. T. Brown *et al.*, "Language Models are Few-Shot Learners," *Advances in Neural Information Processing Systems (NeurIPS)*, vol. 33, pp. 1877–1901, 2020.
13. K. Gupta, P. Bhanodia, et al. "A Review on NFC for Secure Transaction: Its Fundamental Challenges and Future Directions," in *Proc. 2024 Int. Conf. on Advances in Computing Research on Science and Engineering*, 2024.
14. M. Patidar, P. K. Bhanodia, S. Rajput, S. Patel, K. Gupta, and K. K. Sethi, "Efficient Design of Half-Adders and EXOR Gates for Energy-Efficient Quantum Computing with Delay Analysis Using Quantum-Dot Cellular Automata Technology," in *Proc. Int. Conf. on Artificial Intelligence and Sustainable Computing*, Springer Nature Switzerland, 2024.
15. J. Devlin, M. Chang, K. Lee, and K. Toutanova, "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding," *Proceedings of NAACL-HLT*, pp. 4171–4186, 2019.

16. D. K. Sharma, A. Yadav, et al., “Exploring the Impact of Node Velocity on Communication Overhead and Energy Consumption in WSNs Using Fuzzy Clustering,” in *Proc. 2024 Int. Conf. on Advances in Computing Research on Science and Engineering*, 2024.
17. M. Patidar and B. Praveen Kumar, “Advanced Crowd Density Estimation Using Hybrid CNN Models for Real-Time Public Safety Applications,” *Library Progress International (Lib. Pro.)*, vol. 44, no. 3, pp. 16408–16416, 2024.
18. M. Patidar, P. K. Patidar, S. Patel, R. Vijaywargiya, S. Chourawar, D. Mishra, et al., “FitMate AI-Powered Fitness Companion: Revolutionizing Health and Wellness through Technology,” in *Proc. IEEE 4th Int. Conf. on ICT in Business Industry and Government (ICTBIG)*, 2024.
19. R. Yadav, P. Moghe, et al. “Performance Analysis of Side Lobe Reduction for Smart Antenna Systems Using Genetic Algorithms (GA),” *IEEE Xplore*, 2023.
20. M. Patidar, S. K. Shukla, V. Tiwari, G. K. Prajapati, and M. Sahu, “An Efficient Design and Implementation of a Reversible Logic CCNOT (Toffoli) Gate in QCA for Nanotechnology,” *Materials Today: Proceedings*, 2023.
21. D. K. Sharma, P. Goyal, et al. “An Efficient Design and Demonstration of Fault-Effects in Full-Adder Circuits Based on Quantum-Dot Computing Circuits,” *Materials Today: Proceedings*, 2023.
22. M. Patidar, N. Gupta, A. Jain, and N. Patidar, “The Role of Nanoelectronic Devices in a Smart City Ecosystem,” in *AI-Centric Smart City Ecosystems*, Taylor & Francis Group: CRC Press, pp. 85–109, 2023.
23. R. N. Kumawat, M. Patidar, B. K. Mathur, and P. Santra, “Utilization of Harvested Rainwater for Ensuring Green-Fodder Availability in Arid Rajasthan,” *Indian Journal of Agricultural Sciences*, vol. 92, no. 9, pp. 1113–1118, 2022.
24. A. Jain, and A. Tiwari, “An Ultra-Area-Efficient Full Adder Circuits Design Based on Nanoscale QCA Technology,” *Design Engineering*, vol. 2021, no. 9, pp. 3713–3728, 2021.
25. M. Tajammul, M. Adawadkar, and R. Khan, “Integrity Verification Algorithm for Cloud-Stored Documents,” *International Journal of Engineering Research & Technology (IJERT)*, vol. 14, no. 8, Aug. 2025.
26. N. Gupta, “Optimal Energy Estimation of Toffoli and Peres Gate Design Using Quantum-Dot Cellular Automata,” *Research Square*, pp. 1–16, 2021.