Agentic AI for Cloud Troubleshooting: A Review of Multi Agent System for Automated Cloud Support

Kinjal A Patel
Associate Data Scientist
Builure Services Pty. Ltd.
Melbourne, Victoria, Australia
kinjal5721@gmail.com

Eshan Chandra Pandey
Chief Technology Officer
Builure Services Pty. Ltd.
Melbourne, Victoria, Australia
eshanpandey31@gmail.com

Inshu Misra
Chief Executive Officer
Builure Services Pty. Ltd.
Melbourne, Victoria, Australia
inshu.misra@gmail.com

Deepti Surve
Chief Product Officer
Builure Services Pty. Ltd.
Melbourne, Victoria, Australia
surved194@gmail.com

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Abstract **– One of the growing approaches in the field of artificial intelligence is known as agentic AI. This term describes autonomous systems that are meant to pursue complicated goals with minimum interaction from humans. Agentic artificial intelligence displays flexibility, advanced decision-making capabilities, and self-sufficiency, which enables it to work dynamically in contexts that are constantly changing. This is in contrast to traditional artificial intelligence, which is dependent on inflexible instructions and tight oversight. An important step forward in artificial intelligence and contemporary software systems is represented by the development of agentic systems. This development is being pushed by the desire for vertical intelligence that is adapted to a variety of different sectors. Through their capacity for learning, flexibility, and interaction with dynamic settings, these systems improve the results of corporate operations. Large Language Model (LLM) agents, who constitute the cognitive backbone of modern intelligent systems, are at the vanguard of this transformation. They are the agents that are revolutionizing intelligent systems. The aim of this research is to create domain-specific agents to address cloud and SaaS troubleshooting concerns. A particular agent will be created for a designated cloud platform. Manage Personally Identifiable Information to hide data and improve user privacy. This review aims to discuss Agentic AI, its core components, and applications across industries. It also surveys the literature, explores solutions provided by Agentic AI for challenges related to cloud platform failures, examines LLMs as agentic workflows, analyzes the accuracy issues of large language models (LLMs), and presents the proposed methodology along with associated challenges.**

Keywords – Agentic AI, Large Language Model, Cloud Troubleshooting; Artificial Intelligence.

I. Introduction

Artificial intelligence through the agentic approach brings revolutionary changes through self-governing decision systems which operate universally across different industries. The main driving force behind this paradigm change comes from implementing Large Language Model (LLM) agents as the cognitive core of these systems. The development of agentic AI delivers operational improvements along with precise decision making to become a vital component of present-day software programs. Agentic AI carries fundamental aspects as well as practical uses that deal with specific hurdles according to the following content.

The demand for artificial intelligence that is appropriate for a variety of sectors has been the inspiration behind the development of agentic systems, which marks an important milestone in the advancement of AI and modern software systems. Adaptability, learning, and interaction with their dynamic surroundings are the means by which these systems improve the results of corporate operations. Large Language Model (LLM) agents, who represent the cognitive backbone of modern intelligent systems, are at the cutting-edge of this transformation. They are the agents that are revolutionizing intelligent systems [1].

The swift development of technology has brought about changes in the operations of businesses, with software as a service (SaaS) platform becoming important for flexibility and effectiveness across all sectors. Traditional SaaS solutions, on the other hand, frequently fail to match the requirements of domain-specific and ever-evolving needs, despite the fact that companies are facing environments that are becoming increasingly complex and dynamic. Agentic systems have evolved as a new generation of technologies in order to accomplish the objective of bridging this gap. They provide smart, context-dependent, and domain-specific solutions, solving the limits of both standard SaaS platforms and context-aware systems. They are powered by LLMs and sophisticated AI capabilities, and they supply these solutions [1].

Cisco estimates that by 2030, there will be over 125 billion connected devices, necessitating networking solutions to handle large volumes of data and preserve smooth interactions across varied infrastructures. Modern networks require cognitive decision-making systems for autonomous control, adaptive resource management, and real-time optimization to support evolution. Agentic AI is a potential paradigm for autonomous network intelligence designed to overcome challenges of rule-based and static AI infrastructures.

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Agentic AI, developed by OpenAI, DeepSeek, and other research institutions, involves autonomous agents that can understand, reason, act, and learn from their environment. This enables them to optimize network configurations, manage resources, and prevent failures in large-scale systems. Instead of using set rules or pre-trained models, agentic AI uses LLMs, generative AI, and multi-embodied AI agents to create self-organizing, adaptive network topologies [2].

The demand for tools that are intended to be able to function in better but more complicated real-world circumstances while yet allowing for a large amount of flexibility was one of the elements that gave rise to the development of agent-based artificial intelligences. In the fields of disaster assistance, healthcare, and cyber security, for instance, when appropriate judgments are required and the level of disruption is significant, the capacity to govern a situation independently is of the utmost importance. Agentic artificial intelligences not only provide assistance to human actions, but they also improve those actions while taking on work that need a high level of engagement and the ability to multitask without continual human interaction. These kinds of paradigm shifts have the potential to broaden the scope of artificial intelligence, shifting it from being passive and reactive to concentrating on strategic thinking, processing information, and problem solving. This would create the way for a new age, provided that the necessary circumstances are fulfilled [3].

An agent-based artificial intelligence system is anticipated to have a significant influence on society. Agentic artificial intelligence systems would be able to operate alongside people and take on responsibilities that can reallocate human effort, boost productivity, and participate in circumstances where human presence may be undesired or harmful. This would be possible when artificial intelligence becomes increasingly established in fundamental systems and sectors. This transformation has the potential to reshape a position structure in several industries, making it possible for people to work together with artificial intelligence to execute operational duties while people take on positions that are more complicated and strategic [3].

The role of artificial intelligence in agentive AI is very crucial because it serves as a mechanism through which systems are enabled to operate autonomously in addition to augmenting the efficiencies of making decisions and operations in various sectors. Agentic AI integrates advanced machine learning and predictive analytics that make it capable of proactively solving issues and minimizing human input in complex environments.

II. COMPONENTS OF AGENTIC AI & APPLICATION ACROSS INDUSTRIES

AI systems with agentic capabilities demonstrate self-decision-making through environment adaptation and gained knowledge from interaction experiences. This module includes domain-specific inference abilities to generate sector-specific solutions through its Cognitive Skills feature.

Agentic AI through Data Analytics automates analysis tasks and achieves better accuracy which benefits financial sectors and retail industry operations.

Recommender systems benefit from LLM agents which create personalized recommendations through the identification of the relationships that exist between agents [4,5].

III. LITERATURE SURVEY

In [6] Ivens da Silva Portugal et al, Artificial intelligence that uses LLMs to create innovative AI agents that are able to answer questions or work together to accomplish objectives is referred to as agentic AI. These LLM agents have the potential to be utilized in the development of a new generation of recommender models. On the other hand, there is a lack of information on the LLM agents and their relationships, which is necessary for making recommendations. When the framework has been determined, it may then be created. In addition, the processes involved in assessing this framework are not yet fully understood. This research offer a framework for recommender systems that is based on agent-based artificial intelligence and uses many agents. After identifying the LLM agents that have been proposed in the literature, next proceed to determine the relationships between these agents, and finally, suggest a framework that will be used to describe these agents. After that, also conduct an analysis of this framework with regard to the LLM agents and functions of a recommender system by utilizing papers that have been submitted for publication. This work is a stepping stone in the creation of recommender systems, which is a fresh paradigm shift that is currently being explored.

In [7] Nir Kshetri et al, Through the automation of workflows, the enhancement of cooperation, and the improvement of patient outcomes, this article analyzes the role that agentic artificial intelligence plays in the transformation of health care systems. This article addresses how artificial intelligence may be used to overcome inconsistencies and fragmentation in global health care, which can result in lower costs, increased levels of individualized treatment, and improved overall quality of care. The health care industry is characterized by considerable inefficiencies as a result of fragmentation, cognitive overload, and outdated information technology systems, all of which provide challenges to the delivery of high-quality treatment. These challenges have the potential to be addressed by agentic artificial intelligence, which has the ability to streamline processes, improve decision making, and enhance collaboration among people working in the healthcare sector. Artificial intelligence has the potential to improve health outcomes by reducing mistakes, minimizing delays, and optimizing resource allocation. This may be accomplished through the automation of administrative chores and the provision of real-time updates. In the end, the implementation of agent-based artificial intelligence has the potential to convert the health care system into a model that is more efficient and effective. This will be accomplished by promoting financial justice and maximizing patient value.

In [8] Aditi Singh et al, A substantial movement toward agentic procedures in the use of Large Language Models (LLMs) is investigated in this research. This change represents an evolution from the conventional, linear interactions that have been seen between users and artificial intelligence. This study emphasize the usefulness of agentic workflows, which permit a more dynamic and iterative interaction, in enhancing outcomes in activities such as question answering, code development, or stock analysis. This is accomplished through the examination of a case study.

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Four core design patterns are at the heart of the agentic workflow. These patterns include reflection, planning, multi-agent cooperation, and tool use. These components are essential for increasing the productivity of LLM personnel and improving their overall performance. Through the promotion of an iterative and reflective process, the study reveals how agentic workflows might serve as an important step towards the establishment of Artificial General Intelligence (AGI). As research for Artificial General Intelligence (AGI) keeps going, it is becoming increasingly apparent that agentic workflows may be able to offer the critical, incremental steps that are required to accomplish this noble objective. The future relevance of LLMs resides not only in their capacity to generate text, but also in their capacity to participate in self-dialogue, which will push the bounds of artificial intelligence towards levels of sophistication and utility that have never been seen before. Through the adoption of this technique, laying the groundwork for a future in which LLMs will be able to tackle challenging issues in the field of artificial intelligence, which will mark a significant step forward for the academic discipline.

In [9] Yonadav Shavit et al, Artificial intelligence systems that are capable of accomplishing complicated goals with little direct supervision are expected to be of broad benefit if we are able to incorporate them properly into our culture. Despite the fact that such systems have the ability to assist individuals in accomplishing their own objectives in a more efficient and effective manner, they also represent challenges of damage. Within this whitepaper, to propose a definition of artificial intelligence systems, and the parties involved in the life cycle of an AI system. And also emphasize the significance of reaching a consensus on a set of baseline duties and safety best practices for each of these parties. As our core contribution, provide an initial set of standards for ensuring that the operations of agents are both safe and responsible. And expect that these practices can serve as building blocks in the establishment of agreed-upon baseline best practices. There are a number of challenges and doubts regarding the operationalization of each of these activities that need to be resolved before standardization of such practices can occur.

In [10] Satyadhar Joshi et al, The purpose of this research is to give a comprehensive analysis of the most recent artificial intelligence agent frameworks, with particular focus on contrasting their features, architectures, and application cases. Some of the well-known frameworks that investigate are LangGraph, CrewAI, OpenAI Swarm, AutoGen, and IBM Watsonx.Ai. We highlight the positive and negative aspects of these frameworks as well as their applicability to a variety of contexts. In addition, we put the frameworks into categories according to the unique use cases that they are designed for. These categories include open-source frameworks, enterprise solutions, and general-purpose agents. In addition to providing insights into future trends and problems in the development of artificial intelligence agents, the article highlights the significance of adopting the suitable framework to construct autonomous artificial intelligence systems. To offer a performance review of the frameworks that is driven by data by doing an analysis of quantitative parameters such as latency, throughput, and scalability. In addition, to investigate the consequences of these technological breakthroughs in real-world applications, including the influence they have on business automation, risk management, and financial markets. This study is intended to serve as a complete reference for academics and developers who are interested in gaining an understanding of the changing environment of artificial intelligence agent frameworks and the potential for future innovation that they represent. Due to the fact that this is an extremely specialized and fast developing topic, there are not many journal articles available, and this study makes use of white papers and model documents in order to structure this literature review for the purpose of creating peer-reviewed literature. Not more than a year has passed since the majority of the developments that are detailed in this book. The purpose of this research is to give a complete evaluation of AI agent frameworks by classifying the literature according to publication year, category, and area. The tools that are now accessible for the construction of autonomous AI systems are characterized by their fast growth and extensive capabilities, which are highlighted in this thorough analysis of AI agent frameworks. And analyzed both the advantages and disadvantages of a number of well-known frameworks, including LangGraph, CrewAI, OpenAI Swarm, AutoGen, and IBM Watsonx.Ai, as well as each framework's appropriateness for a variety of use scenarios. The findings of our review highlight how important it is to choose the appropriate framework by taking into consideration important aspects like as simplicity of usage, flexibility, connectivity capacity, and enterprise-grade software features.

In [11] Mingzhe Liu et al, LLMs have mathematical skills that are not dependable, which can have a significant influence on decision-making and performance in applications of severe engineering that are connected to buildings. In numerous trials, for instance, LLMs may generate inconsistent replies to similar questions phrased in different ways, following diverse reasoning routes. This is for the reason that LLMs may produce contradictory answers. According to the findings of another study LLMs continue to make errors because of constraints in their knowledge base, reasoning skills, and mathematical computational abilities. It is possible for an LLM-based agentic workflow to integrate rule-based and physics-based tools, such as those found in external calculators, the handbooks published by the American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE), and other similar resources, in order to ensure that trustworthy mathematical calculation tools are activated whenever calculations are required. In addition, an easier technique involves the development of step-by-step procedures that, whenever the developer believes it essential, activate tools that are based on certain rules and physics. However, the present problem is to develop a framework that does not need the use of hardcoding throughout the design process in order to guarantee that tools are called in the appropriate manner when they are required.

In [12] Satyadhar Joshi et al, In this research, an analysis of the top cloud platforms for applications that use generative artificial intelligence is presented. When it comes to Gen-AI Agentic workloads, analyze efficiency, scalability, expenses, and ecosystem support. The demand for cloud infrastructure that is both scalable and stable has considerably grown as a result of the fast development of agent-based generative artificial intelligence (AI). The purpose of this article is to

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provide a comparative study of key cloud platforms, such as Amazon Web Services (AWS), Microsoft Azure, and Google Cloud Platform (GCP), with a particular emphasis on the ability of these platforms to enable applications that leverage agent-based generative artificial intelligence. The scalability of the infrastructure, the cost-effectiveness of the system, and the availability of specialist AI services are some of the major elements that investigate. In addition, we take a look at the significance of well-architected frameworks and best practices when it comes to the deployment of scalable artificial intelligence systems. The future of generative artificial intelligence is also investigated in this research, along with the strategic partnerships and breakthroughs in supercomputing infrastructure that are driving this future. Generative artificial intelligence (GenAI) is quickly altering a variety of sectors, which necessitates infrastructure that is both scalable and cost-effective. A number of cloud platforms, including Amazon Web Services (AWS), Microsoft Azure, Google Cloud Platform (GCP), and Oracle Cloud Infrastructure (OCI), are competing with one another to supply the essential tools and services. The purpose of this literature study is to investigate current papers and articles that describe the capabilities, architectures, and cost considerations of various platforms in relation to the development and implementation of GenAI applications. In accordance with the following categories, we classify these resources: These include: (1) comparative evaluations of cloud platforms; (2) the creation of GenAI infrastructure and applications; (3) methods for retrieval-augmented generation (RAG); and (4) techniques for scalability and cost optimization. In order to offer an in-depth overview of the present status of GenAI in the cloud, the purpose of this evaluation is to highlight the strengths and shortcomings of each platform, as well as identify major developments and challenges.

In [13] Xiaoguang Ma et al, The purpose of this work-in-progress research is to present the AIca demic system, which is a novel framework that makes use of Agentic AI and Agile techniques to improve learning in complicated domains such as computer networks. It is positioned within the area of Artificial Intelligence and Machine Learning Tools to Enhance Instruction, and its objective is to revolutionize the learning experience and outcomes for the complex subject matter. This system places emphasis on active and adaptive learning experiences by utilizing instructional materials that are either created by artificial intelligence or enhanced by AI. Additionally, it incorporates several rounds of feedback and improvement cycles. The AIcademic system creates an interactive artificial intelligence team by utilizing fine-tuned large language models (LLM). This team includes an AIcademic Professor, a Student, and an Instructional Designer, for example. For the purpose of analyzing and simulating real-time classroom interactions from a variety of perspectives, each AI agent is specifically designed using our POISE quick engineering model. Through the use of prompt engineering throughout the process of creating each agent, active learning pedagogy is incorporated into the system. In order to manage collaborations among the AI agents for the purpose of complicated task planning and implementation, feedback integration, output continuous improvement, and agent self-enhancement, the agile approach is utilized. The use of a set of artificial intelligence technologies is being investigated in order to dynamically develop individualized educational materials that are in line with the preferences of the instructor and the requirements of the students. The first findings from a trial deployment of teaching the transport layer in computer networks shown increases in student involvement and comprehension in comparison to the materials that were previously used. A paradigm that is both promising and scalable for the application of artificial intelligence in educational settings is presented by this AIcademic framework. Although it is still in the process of being developed, the purpose of this research is to refine and build upon these discoveries by investigating the full potential of merging Prompt Engineering with Agentic AI for the purpose of establishing active learning environments across a wide range of technologically challenging topics. The implications are not limited to education related to computer networks; rather, they provide a model for redefining teaching and learning in an era that is characterized by the enhancement of technology. We would want to extend an invitation to the wider academic community to work together with us in order to improve the design of the Agent prompt, automate interactions amongst AIs, evaluate the long-term effects, and investigate further uses.

IV. SOLUTION OF AGENTIC AI FOR THE CHALLENGES RELATED TO CLOUD PLATFORM FAILURES

Agentic AI can introduce novel solutions for a number of cloud failure issues that can be resolved with the cloud's capacity for self-coping. Autonomous agents can enable cloud systems to operate more resiliently, predicting points of failure and employing self-healing methods to minimize service downtime while providing reliable service.

Autonomous Operations and AIOps
AI for IT Operations platforms apply automation to complicated operational tasks which drastically cut down maintenance requirements from human operators. AIOps solutions use predictive analytics to study large monitoring data collections that help anticipate node failure events so proactive measures become possible.

Self-Healing Mechanisms
An automated resource state analysis through multi-agent systems helps cloud infrastructures perform recovery strategies such as checkpointing and resource migration independently from external human participation.
Resource healing operations become transparent throughout cloud services due to integrating autonomic computing principles.

Reliability and Optimization
Service-Oriented Reliability implements adaptive reliability modeling together with autonomous optimization approaches which operate in dynamic cloud environments to maintain service availability stability.
Artificial intelligence techniques which integrate anomaly detection with autonomous scheduling abilities leads to better utilization of resources as well as operation efficiency improvement.

The beneficial solutions agentic AI presents for cloud platform failures need further investigation about trustworthy

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system design and system interpretability as these factors are essential for broad adoption and successful implementation [14,15,16,17].

V. LLM AS AGENTIC WORKFLOW

Large Language Models (LLMs) are storing increasing importance in diverse fields such as medicine, education, marketing, and even software engineering, mostly due to their potential to induce transformative impacts. These capabilities facilitate enhanced decision making, improved user experiences, and the creation of novel solutions to complex issues.

A process that involves many LLM agents is referred to as the agentic LLM workflow. The design pattern of this process contains the following elements: reflection (self-assessment), tool usage, planning, and multi-agent collaboration. The potential of LLMs is considerably improved by this approach, which makes it possible to make decisions that are decentralized and coordinated across a variety of aspects of complex systems, including building energy systems. Within the context of an LLM-as-agent workflow, LLM agents communicate with one another as well as with non-LLM components, such as rule-based and physics-based systems in buildings. a makes it easier to coordinate coordinated efforts to manage complicated engineering processes in buildings. By way of example, it has been demonstrated that an LLM-as-agent architecture may automate Building Energy Modeling (BEM) by turning building descriptions into EnergyPlus models. There are four key agents that make up the workflow. These agents are as follows: (1) building description pre-processing, (2) IDF object extraction, (3) IDF object generating suite, and (4) IDF debugging. The duties are broken down into small pieces by these agents, who also guarantee that the outcomes are accurate [11].

VI. ISSUES OF LARGE LANGUAGE MODEL (LLM) IN TERMS OF ACCURACY

Large Language Models (LLMs) create substantial accuracy problems as they work across educational, decision-making and healthcare and scam detection areas. The efficiency enhancement capabilities of LLMs come with a tradeoff of reliability because they exhibit biases alongside inconsistencies and vulnerabilities.

Inconsistency in Evaluations
The evaluation results from LLMs tend to vary considerably particularly when used in educational assessment because changes in model structure and prompting methods result in different outputs. Reduced human evaluator agreement demonstrates the importance of thorough model assessment.

Bias in Decision-Making
The implementation of LLMs generates biases that produce substandard decision results in essential situations. The utilization of LLMs for making decisions increases the chance of delivering incorrect recommendations because of the need for responsible AI implementation.

Vulnerabilities in Specific Applications
Healthcare operations encounter obstacles from inadequate evaluation standards for LLMs during their medical task assessment process. The ability of LLMs to identify adversarial messages in preventing scams is compromised by their high error rates in such situations.

The proper calibration and evaluation of LLMs enables researchers to demonstrate their value in delivering meaningful insights and efficiency improvements according to certain experts [18,19,20,21].

VII. PROPOSED METHODOLOGY

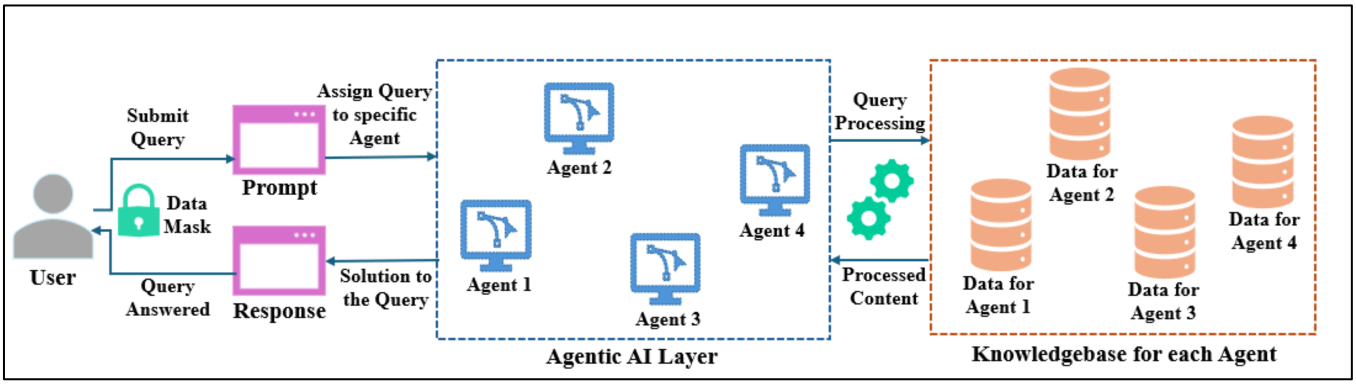

***Fig 1**. Proposed Methodology*

A multi-agent AI system operates through an architectural model shown in the Fig 1 that enables the distribution of problems among AI experts designed for particular roles. The system contains these following components.

1. **User Interaction**:
   - The user submits a query.
   - Before processing the data receives a protective strip that guarantees privacy together with security protection.
2. **Prompt & Response Handling:**
   - The Prompt module receives the query before it distributes the assignment to a particular AI agent.
   - The processed system delivers the Response containing the solution to the user after completion.
3. **Agentic AI Layer:**
   - The AI Agents system contains Agent 1 Agent 2 Agent 3 and Agent 4 among its members.
   - The different agents within the system concentrate on managing particular inquiry types.
   - After assignment the responsible agent executes the query through its available knowledge.
4. **Knowledgebase for Each Agent:**
   - Each agent stores its information through organized knowledge bases.

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- Each agent performs retrieval of data that is relevant to its associated knowledge base.
- The AI layer receives processed content in order to generate a response.

5. **Query Processing:**

- The committed agent uses the knowledge base to obtain needed information before processing it.
- The processed content returns to the AI layer before a response is constructed.

Overall Functionality:

The system conducts user query handling with a specialized AI agent method that focuses separate AI agents on managing specific knowledge areas. The privacy features provided by data masking work together with an efficient domain-specific information retrieval structure.

VIII. CHALLENGES

Agentic AI systems face several significant challenges that impact their security, reliability, and overall effectiveness. These challenges stem from their inherent autonomy, complexity, and the environments in which they operate. The following sections outline the key issues identified in the literature.

Security Vulnerabilities

The direct access that agentic AI systems maintain to databases makes them vulnerable to unauthorized data recovery while their system weaknesses get exploited thus creating potential breaches in data security.

AI systems contain such complex immune systems that make them vulnerable to adversarial attacks which disrupt their choice-making operations.

Decision-Making Challenges

The difficulty for autonomous agents in making sophisticated logical conclusions remains a challenge when operating in changing operational environments. Traditional training methods produce accumulating mistakes thus companies need novel solutions including guided Monte Carlo Tree Search to improve results.

These substantial hurdles to address enable developments of better AI security structures and enhanced decision-making programs. The solution to these weaknesses will result in improved performance of trustworthy agentic AI systems.

IX. CONCLUSION

The review discusses how Agentic AI serves as a solution for industrial challenges while it helps to prevent cloud platform breakdowns and supports agentic workflows that employ large language models (LLMs). A detailed analysis of Agentic AI core technology reveals its potential to enhance accuracy and reliability within AI systems while the study includes both component analysis with its application and literature review. The main challenges which persist regarding Agentic AI involve biases in the system alongside issues of interpretability and restricted computational capabilities. The methodology proposed to tackle these problems will enable better and effective Agentic AI solutions. Additional research needs to improve the methodologies through operational refinement steps and test their practical application to achieve better AI autonomy and reliability results.

The practical limits of this research include the necessity for ongoing modification and training of present agentic AI models, since agents must be updated in accordance with new developments and governmental regulations that necessitate changes in some aspects of personally identifiable information (PII). If agents cannot resolve such concerns, a human expert will address the challenge, necessitating the establishment of a community of experts to get the necessary details for authorized specialists while managing the scheduling flow and expert availability, which presents a further challenge.

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