A Systematic Literature Review of Large Language Model-based Agentic Systems: Development Approaches and Industrial Applications

1st Dunja Kobiljski
Department of Industrial Engineering and Management Faculty of Technical Sciences, University of Novi Sad
Novi Sad, Serbia
dunjakobiljski@uns.ac.rs

2nd Danijela Ciric Lalic
Department of Industrial Engineering and Management Faculty of Technical Sciences, University of Novi Sad
Novi Sad, Serbia
danijela.ciric@uns.ac.rs

3rd Teodora Vuckovic
Department of Industrial Engineering and Management Faculty of Technical Sciences, University of Novi Sad
Novi Sad, Serbia
teodora.vuckovic@uns.ac.rs

4th Dusanka Dakic
Department of Industrial Engineering and Management Faculty of Technical Sciences, University of Novi Sad
Novi Sad, Serbia
dakic.dusanka@uns.ac.rs

5th Darko Stefanovic
Department of Industrial Engineering and Management Faculty of Technical Sciacnes, University of Novi Sad
Novi Sad, Serbia
darko.stefanovic@uns.ac.rs

***Abstract*—Large Language Model (LLM)-based agents represent a rapidly emerging paradigm within agentic artificial intelligence, enabling autonomous, goal-oriented systems capable of complex reasoning and interaction. Despite growing research interest, existing literature remains fragmented, often focusing on conceptual surveys, simulations, or isolated domain-specific applications. This paper presents a systematic literature review of applied and conceptualized LLM-based agentic systems, with a particular focus on development approaches and their manifestations across industrial domains. Studies published from 2021 onward were analyzed to identify trends in industrial application, the usage of open-source development frameworks and enterprise platforms, and emerging research gaps. The results indicate a strong recent growth in applied research, a clear predominance of proof-of-concept implementations, and adoption of open-source frameworks as the most frequently used development approach. The overall findings of this study highlight the need for future research on large-scale solutions, ready for production deployment and systematic evaluation of enterprise platforms in applied agentic systems.**

Keywords*— *artificial intelligence, agentic AI, large language models, LLM agents, development frameworks, enterprise platforms, industry

I. Introduction

Large Language Model (LLM)-based agents have rapidly emerged as a milestone in the evolution of agentic artificial intelligence and artificial intelligence (AI) in general [1]. Agentic AI, as a broader paradigm, enabled transition from static models that lack autonomy and are usually designed for automation of individual steps, to autonomous entities capable of connecting these steps, tracking progress, recovering from errors, and automating any end-to-end process. By integrating the "human-level intelligence" of LLMs into agentic architectures, this new paradigm reshaped AI agents and gave them the ability to perform complex reasoning, planning, independent decision-making and empowered their goal-oriented behavior [2]. Apart from autonomy, as one of the core behavioral principles of LLM-based agents, enabling them to initiate actions [1] and interact with their environment with minimal human intervention [3], these systems also feature proactive, adaptable and collaborative behavior [1].

The research landscape for agentic systems has experienced a profound and accelerated surge in recent years. Search data confirm a sharp spike in interest in agentic AI beginning in early 2024, reflecting a global movement toward building systems that can perform real work through autonomous workflows rather than just simple text generation. As a result of the massive potential of including cognitive skills in agentic entities, there has also been a rapid growth in research efforts related to LLM-based agents [1]. Despite this explosion in research, academic literature remains fragmented. An examination of existing review articles reveals that current research typically falls into the following categories: broad surveys on agentic AI in general, or highly domain-specific studies, focused on exploring application of LLM-based agents in model simulations, or their usage in specific industry domains, without observing a broader industrial spectrum and anticipating trends in LLM-based agent application across different industrial verticals. To address this fragmentation, this systematic literature review (SLR) tends to analyze studies that apply or conceptualize implementable LLM-based agentic systems within specific industry domains, as well as to present cross industry analysis. Additionally, there is still a lack of systematic evidence identifying dominance of different development approaches within applied LLM-based agentic solutions. Therefore, this paper aims to identify the most frequently used open-source development frameworks and enterprise platforms, as well as to examine their manifestations across industry verticals and determine technology maturity and developer trust in different ecosystems.

II. Background and Related Work

A. Evolution of LLM-based agents

Observing the evolution of AI and its transition toward agentic AI, it becomes evident that this occurrence is not sudden, but a result of a multi-decade evolution and development in computational intelligence. Evolution of LLM-based agentic systems is tightly related to AI evolution itself and all technological breakthroughs that preceded agentic AI. Early AI systems were predominantly rule-based, relying on manually defined logic and expert knowledge, which limited their adaptability and scalability. The shift toward machine learning (ML) in the 2000s enabled learning from data which resulted in data-driven decision making and enhanced pattern recognition [3]. However, these systems remained dependent on human intervention and instructions [4]. Manifestations of such systems are predictive analytics models, as well as recommendation engines and robotic process automation tools [5]. Deep learning and transformer architectures in the 2010s further advanced AI capabilities toward multimodal understanding and generative intelligence [3]. This progression from pattern recognition and content generation to autonomy, goal-directed reasoning, and continuous adaptation laid the conceptual and technological foundation for agentic AI [2].

By integrating the human-like intelligence of Large Language Models (LLMs), together with its advanced language understanding and reasoning capabilities, into agentic architectures, the paradigm has shifted from existing agentic AI to LLM-based agents. This transition extended agentic capabilities, particularly in interpreting complex natural language inputs and enabling seamless interaction with human users [4]. In such agents, LLM provides the system's core intelligence and functions as a central cognitive component [2]. To better understand the value that LLM brings to agentic AI, it is important to explain that these models are predominantly based on transformer architectures and are trained on large-scale textual data, making them capable of learning and capturing linguistic structure, grammar, semantics, and contextual relationships [6]. Therefore, in contrast to the concept of Reinforcement Learning (RL), which is central to many agentic systems and enables agents to adaptably learn through interaction, LLM-based agents leverage complex reasoning to interpret goals and adapt their behavior [4]. Furthermore, LLM-based agents increasingly play an important role in multi-agent coordination [5]. Multi-Agent Systems (MAS) decompose complex goals into smaller tasks that individual agents can handle, initiating multiple autonomous agents to cooperate or compete toward a shared goal. The integration of LLM-based agents into such architectures enhances coordination, communication, and adaptive decision-making across distributed agents [4]. However, it should be mentioned that LLMs are not designed to solve engineering, technical, and complex mathematical problems and calculations [6]. Also, characteristics of LLM-based agents further expand the characteristics of general agentic AI. Therefore, LLM-based agents are also characterized with human-like intelligence [2], domain knowledge synthesis [7], commonsense and symbolic reasoning [8].

Realization of LLM-based agents can be established through different practices, ranging from fully custom implementations built directly on LLM APIs, through development frameworks that provide structured agent construction, to secure and integrated enterprise platforms and ready-to-use agentic solutions emphasizing ease of use. However, this paper primarily focuses on open-source development frameworks and enterprise platforms, as they represent structured, yet customizable approaches for realizing LLM-based agents. While development frameworks, particularly open-source ones, are frequently reported in the literature for implementing or conceptualizing LLM-based agents, existing studies rarely report the use of enterprise platforms, which may be attributed to their recent emergence and slower adoption within academic research. Some of the major development frameworks for implementing LLM-based agents are LangGraph, LangChain, AutoGen, CrewAI, Semantic Kernel and AutoGPT. On the other hand, some of the emerging and currently most popular enterprise platforms that represent secure, integrated, large-scale environments and enable users to design, share and orchestrate LLM-based agents are Google Gemini Enterprise, Microsoft Copilot Studio, Salesforce Agentforce 360 and Microsoft Agent 365 [9]-[12].

B. Related studies

Current literature on LLM-based agents can be categorized into three primary research directions: general surveys and conceptual frameworks, agent-based modeling and simulation (ABMS), and industrial and domain specific applications. General surveys provide foundational definitions and taxonomies, explaining the concept of agentic AI and positioning LLM-based agents within it. Some of the most comprehensive surveys and literature reviews on the topic of agentic AI were conducted by Bandi et al. [2], as well as Hosseini and Seilani [3]. Such detailed and comprehensive surveys make a solid foundation for reviewers entering this scientific field. The second group of surveys focuses on agent-based modeling and simulation (ABMS). Gao et al. [1] systematically reviewed the integration of LLMs into agent-based modeling, while Park et al. [13] explored how LLM-based agents replicate the depth and complexity of human behaviors within social setup. Additionally Hua et al. [14] modeled countries as LLM agents to simulate historical international conflicts and Li et al. [15] described simulation within the macroeconomics system. Research articles covering the application of LLM-based agents within different industries describe how these solutions are used, or could be used, within manufacturing, healthcare, information technologies (IT) and other domains. While Ren et al. [7] and Holland and Chaudhari [16] present manifestation of LLM-based agents in manufacturing, studies focused on leveraging LM-based agents within healthcare are covered by Elmitwalli et al. [17] and Han and Choi [18]. Additionally, Zota et al. [19] and Cao et al. [20] present implementation of LLM--based agents within IT.

III. METHODOLOGY

The goal of this research is to systematically examine and synthesize existing literature on LLM-based agentic systems, with a particular focus on their realization through open-source development frameworks and enterprise platforms, as well as on their application across different industrial domains. To achieve this objective, an SLR was conducted following the guidelines proposed by Kitchenham [21]. The review process was organized into three main phases: planning the review, conducting the review, and reporting. It was guided by a predefined set of research questions, followed by inclusion and exclusion criteria, ensuring methodological rigor, transparency, and reproducibility of the study [22].

A. Planning the Review

The planning phase represents the initial and foundational stage of conducting a systematic literature review (SLR) [23] and involves identifying and justifying the need for a systematic review within a particular research area, as well as clearly defining its scope. Establishing the motivation for conducting an SLR requires an initial examination of existing literature to assess the maturity of the field and identify potential research gaps or fragmentation [24]. Therefore, it was identified that no prior literature reviews are presenting trends in application of LLM-based agents across industry verticals, together with identifying dominance of the open-source development frameworks leveraged for implementing these solutions.

Based on the guidelines from Kitchenham [21] the following research questions are formulated:

- **RQ1:** What trends can be observed in the application of LLM-based agents across different industrial verticals?
- **RQ2:** Which open-source development frameworks or enterprise platforms dominate the implementation of LLM-based agents and how their usage manifests across identified industrial verticals?
- **RQ3:** What future research directions are proposed in relation to applied LLM-based agentic systems?

Web of Science and Scopus were databases used for this systematic literature review, as they provide access to a wide range of reliable, integrated, and multidisciplinary studies. Search terms defined for search in these databases combine terms related to agentic AI and LLM-based agents with representative open-source development frameworks and enterprise platforms as shown below:

("agentic artificial intelligence" OR
"agentic AI" OR
"AI agents" OR
"LLM-based agents" OR
"large language model agents" OR
"autonomous agents" OR)
AND
("AutoGen" OR
"AutoGPT" OR
"CrewAI" OR
"LangGraph" OR
"LangChain" OR
"Semantic Kernel" OR
"Microsoft Copilot Studio" OR
"Gemini Enterprise" OR
"Agentforce 360" OR
"Agent 365")

Inclusion criteria defined for this review are:

- **IC1:** The papers presenting studies which conceptualize LLM-based agentic solution within a specific industry domain or describe actual implementation of such solution within a specific industry domain.
- **IC2:** The full text of a publication accessible through the Kobson platform.
- **IC3:** The papers published from 2021 onwards.
- **IC4:** The papers written in English.
- **IC5:** The papers published as a journal article or journal review article.

Exclusion criteria defined for this review are:

- **EC1:** Duplicate papers found in different databases.
- **EC2:** Papers focused on a general topic of LLM-based agents, without describing conceptualization or implementation solutions within industry domains.
- **EC3:** Papers that focused on applying LLM-based agents for simulation and modeling purposes, as they represent a distinct application paradigm.

B. *Conducting the Review*

The first activity of this phase is identification of a maximum number of primary studies related to the research question, through an unbiased search strategy, which will be included in the systematic literature review [25]. Following the inclusion and exclusion criteria, primary studies were identified, and the process of selecting the final set of papers to be analyzed is presented in Table I. Since the selection process was conducted primarily on the Web of Science dataset, Scopus records were used mainly as a complementary source to identify additional relevant studies. An overlap between the two databases was observed, with multiple Scopus records being duplicates of papers already selected from the Web of Science. This explains the difference in the number of selected studies from each of the databases. It should also be mentioned that all selected primary studies from both databases were published as journal articles. Although several review articles were identified during the screening phase, none of them were included in the final selection as they predominantly addressed general concepts of agentic AI and LLM-based agents, without focusing on their implementation within specific industry domains.

C. *Data Extraction and Synthesis*

The primary studies selected through the previous phases of the systematic literature review are summarized and analyzed in this section using the data extraction strategy. As shown in Table II, the overwhelming majority of the selected primary studies were published in 2025 (81%), while only 19% of the studies were published in 2024 and no selected studies were published in 2021, 2022, 2023 and 2026. An important information is that this survey was conducted in early 2026, which leads to a reasonable conclusion that papers on this topic are not yet published in 2026. The strong concentration of publications in the most recent years highlights the rapid emergence and growth of interest in LLM-based agentic systems, particularly in the context of their manifestation within different industries, as well as technological maturity and adoption of large language models.

The type of contribution was extracted for each primary study, as shown in Table III, in order to distinguish between studies that are describing implemented LLM-based agentic systems and studies that propose conceptual or architectural solutions without actual deployment. It is identified that the majority of the papers presented a description of an actual deployment of LLM-based agentic solutions, in a form of proof-of-concept.

TABLE I. FLOW OF EXLUSION AND INCLUSION PROCESS

Database	Results Found	Selected Based on Inclusion and Exclusion Criteria
Web of Science	119	12
Scopus	82	4

TABLE II. DISTRIBUTION OF PRIMARY STUDIES PER YEAR

Year	Primary Studies	Number of Studies	%
2021	/	0	0
2022	/	0	0
2023	/	0	0
2024	[20], [8], [16]	3	19
2025	[6], [7], [17], [18], [19], [26], [27], [28], [29], [30], [31], [32], [33]	13	81
2026	/	0	0

To answer the RQ1, the distribution of the selected primary studies across industry verticals is presented in Table IV. The largest share of studies belongs to the *Business processes, communication and collaboration* vertical (25%). The *Information technology and digital infrastructure* category includes 3 studies (18.75%), while *Chemical engineering*, *Manufacturing*, *Healthcare*, and *Environmental and natural resources management* are each represented by 2 studies (12.5%). The *Other* category includes one study (6.25%) and covers application of LLM-based agentic solution within a specialized domain of animal training that doesn't belong to any of the aforementioned verticals. The aforementioned shows that researchers are mostly involved in automating business, communication and collaboration processes which confirms the inevitable need of the LLM component of the agentic system for such automations.

Table V presents the distribution of the selected primary studies according to the open-source frameworks and enterprise platforms explicitly reported to be used in the analyzed papers. Identifying used or proposed open-source development frameworks and enterprise platforms provides an answer to RQ2. Observing the frequency of reported open-source frameworks used for implementation or conceptualization the solution and platforms across the analyzed primary studies, it is evident that LangChain and CrewAI show the dominance (25% and 18.75% respectfully), and are even combined in some of the solutions to complement each other. The choice of implementation approach most likely primarily correlates with the use case to be established, which suggests that framework dominance may be driven by solution characteristics as a major factor, rather than by general market dominance or superiority of a particular framework. An important observation is that none of the analyzed primary studies reported the use of any enterprise platform as the primary tool for implementing or conceptualizing LLM-based agentic systems. Apart from open-source frameworks and enterprise platforms, it is identified that some of the papers (18.25%) propose custom, author-defined approaches, while the same number of papers do not explicitly define development approach for implementation or conceptualization.

TABLE III. DISTRIBUTION OF PRIMARY STUDIES PER YEAR

Type of Contribution	Primary Studies	Number of Studies	%
Conceptualizatio n	[6], [7], [19]	3	18.75
Implementation	[8], [16], [17], [18], [20], [26], [27], [28], [29], [30], [31], [32], [33]	13	81.25

TABLE IV. DISTRIBUTION OF PRIMARY STUDIES PER INDUSTRY VERTICAL

Industry Vertical	Primary Studies	Number of Studies	%
Information Technology and Digital Infrastructure	[19], [20], [30]	3	18.75
Chemical Engineering	[29], [32]	2	12.5
Manufacturing	[7], [16]	2	12.5
Business Processes, Communication and Collaboration	[6], [8], [27], [31]	4	25
Healthcare	[17], [18]	2	12.5
Environmental and Natural Resources Management	[28], [33]	2	12.5
Other/Specific Domains	[26]	1	6.25

Table VI summarizes the distribution of reported open-source development frameworks and enterprise platforms across the identified industry verticals, which additionally addresses RQ2. As mentioned above, there is no manifestation of enterprise platform reported, while usage of open-source development frameworks across industry verticals seems to be diverse, not showing outstanding dominance of any of the frameworks. Only LangChain appears to be used within four different industry verticals, which is more frequent compared to other frameworks appearing within two verticals and aligns with its dominance within reported frameworks.

TABLE V. DISTRIBUTION OF PRIMARY STUDIES DEVELOPMENT APPROACH

Development approach	Primary Studies	Number of Studies	%
LangGraph	[26], [30]	2	12.5
LangChain	[16], [18], [29], [33]	4	25
AutoGen	[28], [32]	2	12.5
CrewAI	[17], [18], [31]	3	18.75
No Enterprise Platforms Defined	[6], [7], [8], [16], [17], [18], [19], [20], [26], [27], [28], [29], [30], [31], [32], [33]	16	100
Custom, Author-defined Approach	[8], [20], [27]	3	18.75
No Development Approach Defined	[6], [7], [19]	3	18.75

TABLE VI. USAGE OF OPEN-SOURCE DEVELOPMENT FRAMEWORKS AND ENTERPRISE PLATFORMS ACROSS INDUSTRY VERTICALS

Industry Vertical	Development Approach
Information Technology and Digital Infrastructure	LangGraph
Chemical engineering	LangChain, AutoGen
Manufacturing	LangChain
Business processes, communication and collaboration	CrewAI
Healthcare	LangChain, CrewAI
Environmental and natural resources management	LangChain, AutoGen
Specific domains	LangGraph

IV. Discussion

This section interprets the findings derived from the data extraction and synthesis phase, relating them to the formulated research questions and positioning them within the broader context of research on LLM-based agentic systems, aiming to identify research gaps and potential future research directions.

The strong concentration of selected primary studies published in 2025 (81%) clearly indicates that applied research on LLM-based agentic systems is in a very early yet rapidly accelerating phase. The absence of studies in 2021, 2022 and 2023, combined with the sharp rise observed in 2024 and 2025, suggests that the maturity of large language models and the availability of appropriate tools were necessary preconditions for applied research to emerge. The observed trajectory strongly suggests continued growth throughout 2026, particularly in exploratory and experimental studies. Future research is expected to increasingly address open challenges identified in recent literature, including cost-efficient and scalable deployments of agentic systems [5], the definition of standardized evaluation metrics for agent performance in simulation and modelling [1], cybersecurity vulnerabilities in agentic architectures, and questions of shared responsibility and accountability between developers, users, and autonomous agents [34].

The predominance of studies oriented on implementation of LLM-based agents (81.25%) demonstrates that the research community has moved beyond purely conceptual discussions toward hands-on experimentation. However, an important nuance revealed by the analysis is that all reported implementations were conducted at a proof-of-concept and prototype level. This suggests that while interest and technical feasibility are well established, the field has not yet transitioned toward large-scale, production-grade deployments. As agentic AI continues to gain visibility and organizational relevance, it is expected that future studies will propose both - more refined conceptual architectures and implemented systems that go beyond experimental settings.

The distribution of studies across industry verticals provides an answer to the first research question (RQ1) and reveals a clear emphasis on business processes, communication, and collaboration, followed by IT and digital infrastructure. This dominance can be attributed to the natural alignment between LLM capabilities and tasks that are language intensive and require coordination, where automation and decision support provide immediate value. Domains such as chemical engineering, manufacturing, healthcare, and environmental management are also represented, indicating growth of this topic across different disciplines. As LLM-based agents mature, future research is likely to expand into additional domains such as logistics, education and legal service, where complex workflows, regulatory constraints, and collaboration present suitable ground for agentic systems. Observing distribution of development and implementation approaches of LLM-based agents, it should be highlighted that the selection of a specific development framework or other tools could be driven by requirements specific to a use case explored, as well as researcher expertise, rather than by the inherent superiority of any single solution. Different frameworks support different architectural styles, making suitability a dominant factor in implementation decisions. However, the findings indicate a clear orientation toward open-source development frameworks, while fully custom implementations are less represented and enterprise platforms are not leveraged at all. Therefore, to answer RQ2, most frequently used open-source development frameworks are LangChain (25%), CrewAI (18.75%), LangGraph (12.5%) and AutoGen (12.5%) Although no single open-source framework demonstrates overwhelming dominance across all studies, frameworks such as LangChain and CrewAI appear more frequently than others, even complementing each other in some solutions. This recurring usage can be interpreted as an indicator of ecosystem maturity, community adoption, and developer trust, next to the mentioned use case suitability. In contrast, enterprise platforms were not reported as the primary implementation environment in any of the analyzed studies. This may be attributed to their relatively recent emergence, proprietary nature, as well as limited transparency, and accessibility for academic experimentation. This absence does not directly imply irrelevance but rather highlights a gap between market growth together with industrial experimentation and academic reporting. The cross-analysis of open-source frameworks and enterprise platforms usage across industry verticals reveals that no framework shows significant dominance pattern. Instead, different frameworks appear across multiple domains, almost in relatively comparable proportions, reinforcing the conclusion that framework selection is guided by task characteristics rather than industry affiliation. The only framework occurring more frequently is LangChain, which aligns with its higher usage among other open-source frameworks reported, which suggests its applicability across different use cases and potential ecosystem maturity and community adoption. Enterprise platforms, as previously mentioned, do not appear in any industry vertical as a reported implementation or conceptualization tool, further emphasizing their limited adoption within academic research at the time of this review.

Beyond previously identified challenges related to evaluation, ethics, security, and responsibility, this review identifies a critical gap in the operationalization of LLM-based agentic systems as an answer to the RQ3. The dominance of proof-of-concept implementations indicates that large-scale and production-ready deployments remain underexplored. Future research should focus on validating framework maturity through real-world, long-term deployments, addressing scalability, reliability, governance, and lifecycle management. In this context, enterprise platforms may emerge as a viable implementation option, offering support on the infrastructure level, as well as support for deployment, monitoring, and compliance. Systematic investigation of such platforms, alongside hybrid approaches combining open-source frameworks with enterprise tooling, represents a promising and yet unexplored research direction.

V. Conclusion

This systematic literature review examined the application of LLM-based agentic systems across industry verticals, with a particular focus on open-source development frameworks and enterprise platforms. The results indicate that research in this area is recent and rapidly growing, with the majority of studies published in 2025 and oriented toward proof-of-concept implementations. While applied research is already present across multiple domains, large-scale, and solutions ready to be deployed to production remain unexplored. The findings show that open-source development frameworks dominate reported implementations, with no single framework exhibiting significant dominance across industries.

Framework selection is most likely driven primarily by use case requirements and researcher expertise rather than by inherent superiority or overall preference of a particular framework. In contrast, enterprise platforms were not reported as implementation or conceptualization tools within the analyzed studies, suggesting limited adoption within academic research. This work highlights important gaps related to operationalization, scalability, and validation of LLM-based agentic systems, providing a foundation for further investigation into the maturity and industrial adoption of LLM-based agents. Future research should focus on transitioning from experimental prototypes toward production deployments, as well as on systematically exploring the role of enterprise platforms and hybrid approaches.

THE USE OF AI

During the preparation of this work, the authors used ChatGPT (GPT-4) to improve readability and language usage. The authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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