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Towards Intelligent Requirements Engineering: A Systematic Review of AI-Enabled Solutions

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Abstract: Requirements Engineering (RE) is an important stage during software development which aims to explore, analyze, validate, prioritize and manage the requirements of stakeholders prior to the system implementation. Traditional RE approaches suffer from problems of natural-language ambiguity, evolving needs, extensive documentation, conflicting views among stakeholders, and low levels of automation. This Systematic Literature Review (SLR) examines 43 studies to gain an understanding of the role of Artificial Intelligence (AI) in improving RE activities. AI technologies such as Natural Language Processing (NLP), Machine Learning (ML), Large Language Models (LLMs), Generative AI (GenAI), prompt engineering, knowledge graphs, ontologies, optimization algorithms, and multi-agent systems are increasingly being used, as highlighted in the review. AI is being broadly utilized in the requirements elicitation, analysis, specification, validation, prioritization, traceability, and semantic management. NLP and ML are integral to text analysis and classification, and LLMs and GenAI are vital to automated requirement generation, documentation, and validation. Intelligent and integrated RE frameworks, such as knowledge-graph approaches, ontology-based models and automated multi-agent systems are emerging trends. There are, however, problems like hallucination, explainability, sensitivity to prompts, privacy issues, ethical concerns, poor reproducibility, and lack of validation in industry that are still a barrier to adoption. The study found that while the use of AI in RE is promising, it needs expert oversight, thorough testing, and practical solutions to be ready for the market.

Keywords: Artificial Intelligence; Requirements Engineering; Systematic Literature Review; Natural Language Processing; Machine Learning; Large Language Models; Generative AI; Prompt Engineering; Knowledge Graphs; AI-Enabled Software Engineering

1. Introduction

Requirements Engineering (RE) is a key activity in the Software Development Life Cycle (SDLC) since it involves defining, analyzing, documenting, validating and managing the requirements and expectations of the stakeholders before the system is built. The RE process provides a solid foundation that enables software teams to comprehend the system's intended functionality, constraints it needs to adhere to, and how user requirements should be articulated with functional and non-functional requirements [22], [39]. RE is, however, a difficult activity as requirements are frequently given in natural language, which can be hard to understand, ambiguous, incomplete, or inconsistent [3], [11]. These problems are exacerbated in today's software development process through the use of complex software systems, evolving stakeholder needs, agile software development methods, large-scale requirement documents, and evolving systems [24], [35]. The improper management of requirements can have negative impact on software quality, raise project development cost, cause delay of project and make the stakeholders less satisfied with the project, so it has become an important research issue of software engineering [22], [24].

Artificial Intelligence (AI) is considered an important research direction to enhance and automate Requirements Engineering (RE) activities in recent years. AI-powered solutions can be categorized into methods that are useful for various RE tasks, including: Machine Learning (ML), Natural Language Processing (NLP), deep learning, recommendation systems, optimization algorithms, knowledge graphs, ontologies, Large Language Models (LLMs) and Generative AI (GenAI) [2], [11], [19]. The NLP based approach is more valuable due to the fact that a number of requirements are usually expressed in natural language, and NLP can be used in order to find defects, extract domain concepts, classify requirements and provide traceability for textual requirement documents [11]. Recently, LLM and GenAI technologies like ChatGPT have been leveraged for requirements elicitation, analysis, specification, validation, prioritization, modeling, and documentation due to their capacity to comprehend and produce human-like language [6] [10] [40]. Prompt engineering and multi-agent LLM frameworks have also been identified as novel ways to enhance the reliability and usefulness of RE support via LLM [7], [9].

AI-based Requirements Engineering is receiving much attention in the research community, however, the state of the art is still scattered over techniques, tools and activities in RE. There are some studies concerned with NLP for RE [10], some focusing on AI-based requirements prioritization [11], some on LLMs and ChatGPT [19], some on GenAI-based RE [29], and some on RE for AI-based systems [40] and tool support for RE [42]. This fragmented evidence hinders the ability to get a picture of the full extent to which AI is being used in the RE process. Furthermore, the current research indicates that the utilization of AI and GenAI applications in RE is unevenly spread across the various RE phases: Elicitation and Analysis seem to be getting more focus, whereas Requirements Management and Industrial Integration are less explored [42]. Other significant challenges raised in the literature are the interpretability of the requirements artifacts generated by AIs, prompt sensitivity, lack of controllability, data dependency, lack of human oversight in AI-generated artifacts, and hallucination [9], [40], [42], [43].

The problem in this study is that of lack of consolidated and structured understanding in the field of Requirements Engineering of solutions enabled by the use of Artificial Intelligence. Although numerous approaches have been suggested based on artificial intelligence for the individual RE tasks, scholars and practitioners require a better understanding of the role played by the AI techniques in the different RE tasks, the value added by them, the challenges they pose and the future directions for the field. The rapid development of LLMs and GenAI creates new opportunities and risks for RE: the LLM outputs are unreliable, requirements can be hallucinated, the LLM is not always explainable and uncertainty in real-world use of the LLM.RE problem is important as it is related to new opportunities and risks of the rapid development of LLMs and GenAI: unreliable outputs, hallucinated requirements, limited explainability, uncertainty in real world usage. Without a systematic review, it is hard to identify trends, compare different approaches, assess the maturity of AI-supported RE solutions, and direct future research on more reliable, explainable and practically useful AI-enabled RE solutions.

To solve this issue, this paper, "Towards Intelligent Requirements Engineering: A Systematic Review of AI-Enabled Solutions," systematically reviews 43 selected papers related to AI-supported and AI-driven Requirements Engineering. This is the first work to categorize the literature into the AI techniques used in RE, the activities in RE that they support, the benefits they provide, and the limitations they pose. This review also identifies key research gaps, such as lacking industrial validation, low level of integration into real RE workflow, lack of explain ability, risks of hallucination and lack of support for some phases of RE. This paper brings together the results of the various studies conducted around this issue, and suggests future research pathways to build more intelligent, trustworthy and industry-relevant RE solutions. In summary, the study suggests that AI holds significant promise for advancing Requirements Engineering, but its effective implementation and application need to be carefully validated, involving human input and addressing ethical issues and reliable evaluation methods.

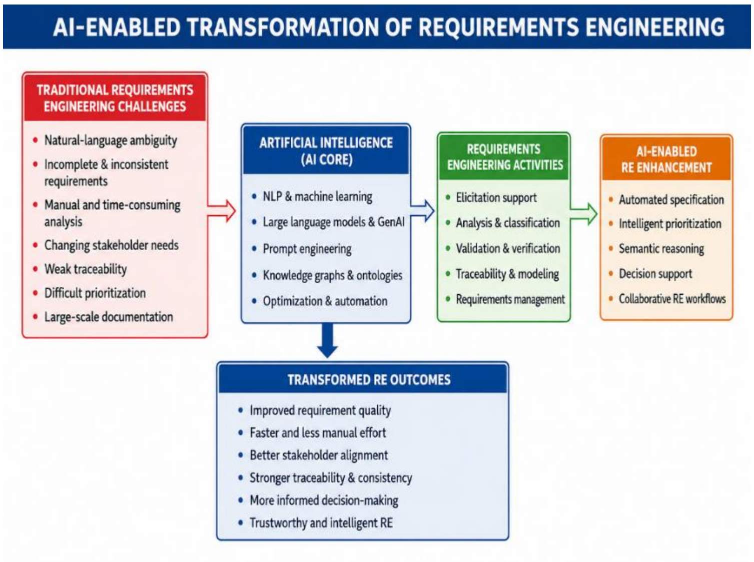

Figure 1. Conceptual Framework for AI-Enabled Transformation of Requirements Engineering

2. Related Studies

This is the top five most relevant studies of the topic "Towards Intelligent Requirements Engineering: A Systematic Review of AI-Enabled Solutions" that has been selected for the subject. These research studies were selected because they are directly related to the use of AI, NLP, LLM, GenAI, prompt engineering, and knowledge-based methods in Requirements engineering. The table presents a comparison of each paper by its reference number, title, focus of the survey, year of publication, teaching and learning approach of the survey, and whether or not there is a quality assessment, a research framework, teaching and learning tools, and content coverage. The selected studies contain [42] and [18] as the latest 2026 contributions and the former studies [10], [9] and [11] provide solid background on LLMs, Prompt Engineering and NLP-Requirements Engineering.

Table 1. Related Studies

Ref.	Focus of Survey	Publish Year	Survey Approach	Research Framework	Teaching and Learning Tools	Content
[18]	Focuses on AI-driven requirement extraction/classification, explicit and implicit requirements, NLP, ML, BERT, BiLSTM, class imbalance handling, and Knowledge Graph-based semantic representation.	2026	Not a pure survey; it is an AI-enhanced framework/experimental study with related-work synthesis. It uses the PROMISE dataset, eight experiments, and evaluates models using accuracy, precision, recall, and F1-score.	✓	✓	✓
[10]	Reviews how LLMs are	2025	Systematic literature review of	✓	✓	✓

	applied in RE tasks, including elicitation, validation, prompting strategies, artifacts, tools, datasets, evaluation methods, and industrial-use gaps.		74 primary studies from 2023–2024; categorizes publication trends, supported RE activities, prompting strategies, and evaluation methods.			
[9]	Focuses on prompt engineering for RE, including few-shot prompting, chain-of-thought, RAG, constraint injection, multi-role dialogue, RE task mapping, LLM families, prompt types, limitations, and roadmap.	2025	Roadmap-oriented systematic literature review; follows Kitchenham and Petersen protocols, searches six libraries, screens 867 records, and analyzes 35 primary studies.	✓	✓	✓
[11]	Reviews NLP4RE research, including linguistic analysis of textual requirements, language issue detection, domain concept identification, traceability links, NLP tools, techniques, resources, and empirical research trends.	2021	Systematic mapping study guided by five research questions; identifies 404 primary studies, 130 NLP4RE tools, and 231 NLP technologies.	✗	✓	✓

[42]	Reviews GenAI use in RE, covering trends, methodologies, challenges, future directions, RE phase coverage, industrial adoption, hallucination, reproducibility, interpretability, tools/datasets, and benchmarking gaps.	2026	Systematic literature review of 238 articles from 2019–May 2025 using systematic search, data extraction, feature analysis, and RE classification based on ISO/IEC/IEEE 29148:2018.	✓	✗	✓

Table1 indicates that the studies selected in this work give a solid basis to the understanding of the current situation of the requirements engineering area with respect to the use of AI. The reviewed papers include significant topics like GenAI-based RE, LLM-enabled RE activities, Prompt engineering, NLP-based analysis, requirement extraction, requirement classification and knowledge representation [9], [10], [11], [18], [42]. An analysis of the comparability of all studies, however, also indicates that there is no support from all studies for all the dimensions of evaluations. For instance, in the selected studies, content and research direction are given due importance while the importance of teaching and learning tools is not taken into consideration. These five papers, therefore, will be extremely helpful in developing background, gap analysis and justification of the present systematic review, particularly the literature that emphasizes the potential and challenges of AI empowered solutions in the field of Requirements Engineering.

3. Methodology

In the current study, the Systematic Literature Review (SLR) approach has been used to thoroughly study the role, impact, and ongoing advancement of Artificial Intelligence (AI)-based solutions in Requirements Engineering (RE). The aim of the SLR approach is to gather, screen, evaluate and synthesize the existing research systematically and transparently so that the results can give a reliable understanding of the application of AI techniques in various RE activities. The following review concerns the areas of RE with support from AI: Requirements Elicitation, Analysis, Specification, Validation, Prioritization, Traceability, Requirements Modelling, Requirements Management. It also examines the applications of various AI technologies such as machine learning (ML), natural language processing (NLP), large language models (LLMs), generative AI (GenAI), prompt engineering, knowledge graphs, ontology-based methods and multi-agent systems.

A structured review protocol was used to make the review objective, transparent and replicable. The following steps in the review process were carried out: Identification of relevant studies, screening of papers, quality appraisal of selected papers, data extraction, and synthesis. These chosen papers were analysed to identify the techniques of AI they were using, RE activities that they were supporting, the tools or frameworks that they were proposing, the benefits they reported, their limitations and the future research directions. To reflect the latest advancements in AI-based Requirements Engineering, the review focused on pertinent and peer-reviewed research papers published from a specific timeline (2021-2026). The systematic approach guided the organization of the literature, comparison of the current approaches, identification of gaps in the literature, and understanding of the maturity of solutions based on the use of AI in the RE domain.

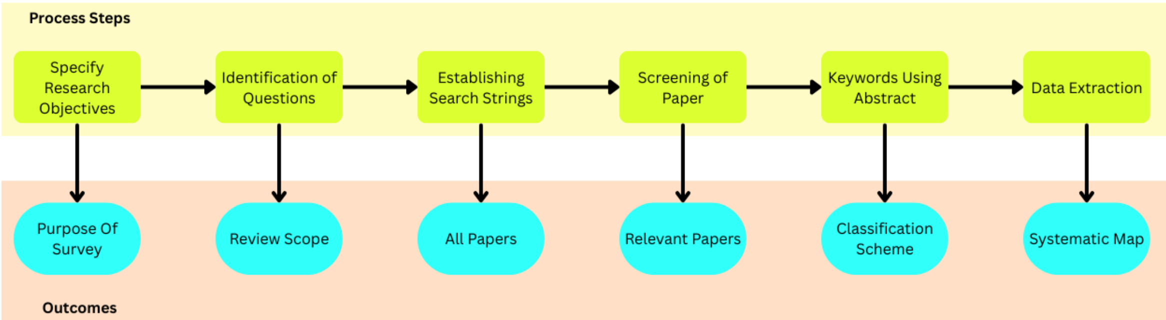

Figure 2. Process Step

The general process used in the SLR in this study is shown in Figure 2. It starts with formulating the research goal and the research questions, then reading through pertinent papers from academic literature and uploading research material. Then, the gathered papers are filtered according to their relevance to the field of Requirements Engineering in the context of AI. Studies that are not specifically related to AI, RE, NLP, LLM, GenAI, Requirements prioritization, Requirements elicitation, Requirements validation, traceability, RE for AI-based system are not included. The rest of the studies are then evaluated based on quality and relevance. Lastly, the chosen studies are analyzed and synthesized in order to obtain meaningful conclusions on the AI techniques, the supported RE activities, challenges, limitations and future directions.

3.1. Research Questions

The aim of this systematic literature review is to formulate research questions that will help the study to run in a focused and structured way. Given the goal of the paper is to investigate AI-supported solutions in RE, the research questions are directed towards identifying the key AI techniques identified in RE, the RE activities supported by these techniques, the benefits and limitations reported in previous studies, as well as the frameworks or models that have been proposed for intelligent RE support. The literature on AI-based Requirements Engineering is spread across several different fields, such as NLP for RE, LLM for RE, GenAI-based RE, prompt engineering, AI-based requirements prioritization, RE for AI systems, knowledge graphs, ontology-based RE and automated RE frameworks, which is why these questions were created. Thus, the research questions establish a transparent relationship between the goal of the study and evidence drawn from the papers selected. Table 2 shows the full list of research questions, objectives and motivations.

Table 2. Research Questions

Research Questions	Objective	Motivation
RQ1: Which top-tier publication sources have contributed to research on AI-enabled Requirements Engineering, and what geographical regions have shown the most scholarly engagement in this domain?	To identify leading publication venues and active geographical regions contributing to AI-enabled Requirements Engineering research.	Understanding publication and regional trends helps recognize dominant contributors, research concentration areas, and gaps in underrepresented contexts within AI-enabled Requirements Engineering.
RQ2: What major Artificial Intelligence techniques, methods, and computational approaches are currently being used to support and improve	To identify the main AI-based techniques used in RE, such as Machine Learning, Natural Language Processing, Deep Learning, Large Language Models, Generative AI, prompt engineering,	Identifying AI techniques helps in understanding the current technological trends and the types of intelligent solutions being applied in Requirements Engineering.

Requirements Engineering processes?	knowledge graphs, and ontology-based approaches.	
RQ3: Which specific Requirements Engineering activities are supported by AI-enabled solutions, and how are these solutions applied across different phases of the RE process?	To classify AI applications across RE activities such as requirements elicitation, analysis, specification, validation, prioritization, traceability, modeling, and requirements management.	This question helps determine which RE phases are well-supported by AI and which areas remain underexplored.
RQ4: What technical, methodological, ethical, and practical challenges limit the effective adoption of AI-enabled solutions in Requirements Engineering?	To identify limitations such as hallucination, lack of explainability, reproducibility issues, prompt sensitivity, data dependency, bias, limited industrial validation, and the need for human oversight.	Recognizing these challenges is important for evaluating the reliability, trustworthiness, and practical readiness of AI-based RE solutions.
RQ5: What AI-enabled frameworks, models, tools, or architectures have been proposed for Requirements Engineering, and how do they contribute to the development of intelligent, automated, and trustworthy RE practices?	To synthesize the proposed frameworks, models, tools, and architectures that support AI-based RE activities, including multi-agent frameworks, automated RE frameworks, knowledge graph models, ontology-based approaches, and GenAI/LLM-based frameworks.	A framework-based question is important because it helps identify structured solutions that can guide the design, implementation, and evaluation of intelligent Requirements Engineering systems.

3.2. Formulation of Search String

The academic databases and research sources were searched for relevant literature with appropriate search terms to perform the systematic literature review of AI-enabled Requirements Engineering. The development of the search strategy involved the retrieval of studies on the use of Artificial Intelligence in the Requirements Engineering and its sub-activities, such as requirements elicitation, analysis, specification, validation, prioritization, traceability, modeling, and management. The search terms were chosen to encompass both classic AI technologies and newer ones like NLP, Machine Learning, Deep Learning, Large Language Models, Generative AI, ChatGPT, prompt engineering, knowledge graphs, ontology-based approaches, and multi-agent systems. Main concepts were combined using boolean operators – AND and OR – to widen or narrow the search results. The final search strings and academic sources selected are displayed in Table 3.

Table 3. Search String

Sources	Search String
Google Scholar, Scopus, IEEE Xplore, ScienceDirect, ACM Digital Library, Springer Link, MDPI	("Artificial Intelligence" OR "AI" OR "Machine Learning" OR "ML" OR "Natural Language Processing" OR "NLP" OR "Deep Learning" OR "Large Language Models" OR "LLM" OR "Generative AI" OR "GenAI" OR "ChatGPT" OR "Prompt Engineering") AND ("Requirements Engineering" OR "Software Requirements" OR "Requirement Elicitation" OR "Requirement Analysis" OR "Requirement Specification" OR "Requirement Validation" OR "Requirement

	Prioritization" OR "Requirement Traceability" OR "Requirements Management")

3.3. Selection-based on Inclusion/Exclusion criteria

The selected academic databases were searched using the developed search protocol and a total of 11,592 research articles were found. After the first filtering, there were 5276 records that were deleted as duplicate, non peer-reviewed or out of scope studies. To assess the relevance to the field of Artificial Intelligence-based software engineering and Requirements Engineering, all remaining 6,316 records were further screened by title and abstract with the result that 3,332 studies were excluded as they were not directly relevant to the field. Following this, 2,984 studies were analysed in further detail and 1,542 of these articles were discarded due to their lack of explicit discussion of AI for RE activities, that is, elicitation, analysis, specification, validation, prioritization, traceability, or requirements management. The remaining 1,442 articles were then further investigated, and 672 of these studies were discarded due to the lack of clear techniques, tools, frameworks, models or methodologies based on AI for Requirements Engineering. This reduced that number to 770 studies that could be reviewed as full text. In full-text assessment, 727 articles were excluded because the study's methodological relevance to the research questions was weak, results were incomplete, the study did not directly address its research questions, or the study did not sufficiently discuss AI-enabled RE solutions. As a result of the screening and exclusion process, 43 quality studies adhere to all the inclusion criteria and are included in the systematic literature review of the final quality studies, as indicated in Figure 3.

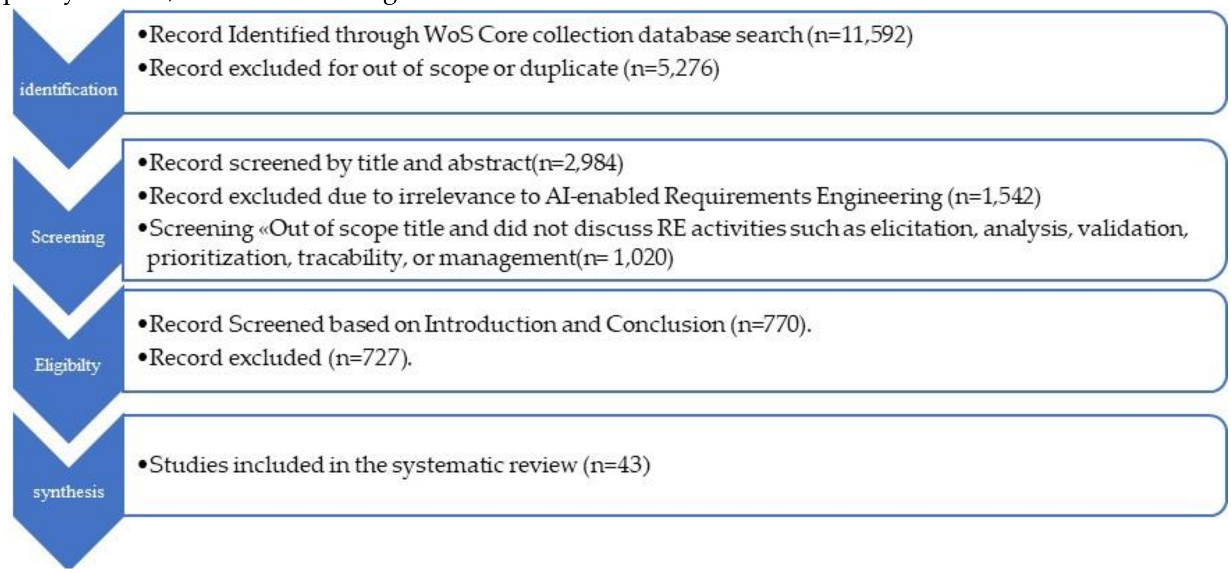

Figure 3. Inclusion Exclusion Criteria

4. Results

RQ1: Which top-tier publication sources have contributed to research on AI-enabled Requirements Engineering, and what geographical regions have shown the most scholarly engagement in this domain?

The research results of AI-enabled RE have been published in various academic journals and conferences, showing that it is not restricted to any one journal or conference. The studies were chosen from the software engineering journals, AI-related journals, Requirements Engineering journals, Springer and MDPI journals, IEEE and ACM conference proceedings, workshop proceedings, book chapters, and arXiv-based research outputs. The diversity of publication sources suggests that AI-supported RE is an interdisciplinary research field related to the fields of Artificial Intelligence, Software Engineering, Natural Language Processing, Large Language Models, Generative AI, and Requirements Engineering. As a way of getting a clearer picture of the publication trend, the 43 studies selected were grouped by journal, conference, workshop, or source name, as indicated in Table 4.

Table 4. Publication Source Distribution

Sr. No.	Journal / Conference / Source Name	No. of Publications

1	arXiv / CoRR	8
2	Software: Practice and Experience (Wiley)	2
3	IEEE Access	2
4	Applied Sciences (MDPI)	2
5	Frontiers in Computer Science	2
6	ACM Computing Surveys	1
7	ACM Transactions on Software Engineering and Methodology	1
8	ACM Conference on Fairness, Accountability, and Transparency (FAccT)	1
9	ACM Southeast Conference (ACMSE)	1
10	IEEE/ACM International Conference on Software Engineering: Companion Proceedings (ICSE-Companion)	1
11	IEEE International Requirements Engineering Conference Workshops (REW / REWBAH)	1
12	IEEE International Requirements Engineering Conference (RE)	1
13	IEEE International Conference on Information Reuse and Integration for Data Science (IRI)	1
14	CEUR Workshop Proceedings — REFSQ Workshops / NLP4RE	1
15	World Scientific Book Chapter: Artificial Intelligence Methods for Software Engineering	1
16	World Journal of Advanced Research and Reviews (WJARR)	1
17	Journal of Theoretical and Applied Information Technology (JATIT)	1
18	Journal of Software Engineering Research and Development	1
19	Journal of Software: Evolution and Process (Wiley)	1
20	Research Square	1
21	ResearchGate Full-Text Research Source	1

22	Mathematical Problems in Engineering (Hindawi/Wiley)	1
23	Madhya Pradesh Journal of Social Sciences	1
24	Pediatric Radiology (Springer)	1
25	Requirements Engineering (Springer)	1
26	Forschung im Ingenieurwesen / Engineering Research (Springer)	1
27	Automotive Engineering / ATZ Worldwide — Springer Professional	1
28	SN Computer Science (Springer)	1
29	Sensors (MDPI)	1
30	European Journal of Advances in Engineering and Technology	1
31	Systems (MDPI)	1
32	Future Internet (MDPI)	1
Total		**43**

Table 5. Geographical Distribution of papers

Sr. No.	Region / Continent	Country	No. of Publications	Total
1	Europe	Germany	4	17
		United Kingdom	4	
		Portugal	2	
		Sweden	2	
		Austria	1	
		Croatia	1	
		Italy	1	
		Spain	1	
		Norway	1	
2	Asia	Pakistan	3	8
		Singapore	1	
		China	1	
		India	1	
		Turkey	1	
		Japan	1	
3	North America	United States	7	7
4	Middle East	Saudi Arabia	2	4
		Jordan	1	
		Iran	1	
5	Oceania	Australia	4	4
6	South America	Brazil	2	2
7	Africa	Egypt	1	1
		Total		43

Table 6. Continents

Continents	Percentage
Europe	40%
Asia	19%
North America	16%
Middle East	9%
Oceania	9%
South America	5%
Africa	2%

From research on AI-enabled Requirements Engineering, there is a wide and interdisciplinary publication pattern: research publications do not limit themselves to one journal, conference or region. The journals and conferences for software engineering, the ones that focus on AI, the ones that are focused on RE, the ones that are book chapters, and the rapid research posts like arXiv/CoRR are the journals and conferences the selected literature has appeared in. This suggests that the topic is evolving and is still in the midst of rapid development, as evidenced by the proliferation of LLM applications, GenAI, prompt engineering, NLP-based RE, and automated RE frameworks. However, the selected body of research is not only dominated by arXiv/CoRR, but also includes other journals and venues, such as Software: Practice and Experience, IEEE Access, Applied Sciences, Frontiers in Computer Science, ACM Computing Surveys, Requirements Engineering, Future Internet, SN Computer Science, and Systems, and Sensors, with the numbers of contributions being presented in Table 4. Geographically, the studies reflect high levels of participation from Europe, followed by Asia and the North American region, and a contribution from the Middle East, Oceania, South America and Africa. As can be seen in the table 5 below, the countries that are visible in selected studies include Germany, the United Kingdom, the United States, Australia, Pakistan, Saudi Arabia and Brazil. This trend is also reflected in the percentage distribution in Table 6, which shows that 40% of respondents are from Europe, 19% from Asia and 16% from North America. In conclusion, these results indicate that RE research has been brought to the attention of AI globally, but is not evenly distributed by region, thus providing opportunities for further involvement of underrepresented regions.

RQ2: What major Artificial Intelligence techniques, methods, and computational approaches are currently being used to support and improve Requirements Engineering processes?

From the reviewed papers, it can be concluded that there is no single technique to support AI-based Requirements Engineering but multiple approaches are used such as language-based processing, language learning, generative, semantic, optimization and agent-based processing. Given that most of RE artifacts are in natural language, there exists a significant amount of literature on Natural Language Processing (NLP) [10] and Machine Learning (ML) [11], deep learning, transformer models, Generative AI (GenAI) [42] and Large Language Models (LLMs) [18] for RE requirements elicitation, analysis, specification, validation, prioritization, and traceability. Furthermore, the selected papers and matrix reveal that other techniques such as knowledge graphs, ontologies, prompt engineering, recommendation models, clustering, optimization algorithms and multi-agent frameworks are also adopted to intelligent, automate and enrich RE, in terms of its semantic aspect. Additionally, the selected papers and matrix indicates that other techniques, such as knowledge graphs, ontologies, prompt engineering, recommendation models, clustering, optimization algorithms, and multi-agent frameworks are being utilized to make RE more intelligent, automated, and semantically rich. The selected studies were analyzed and the technique group categories are explained below and summarized in Table 7.

4.1. Natural Language Processing (NLP) and text mining

NLP is one of the most commonly used AI approaches in Requirements Engineering because requirements are usually written in natural language. NLP techniques are used to process requirement documents, user stories, stakeholder feedback, issue reports, regulations, and technical documents. These techniques support tasks such as requirement classification, ambiguity detection, semantic analysis, information extraction, traceability-link recovery, and structure inference [11]. Zhao et al. mapped NLP4RE research and identified a wide range of NLP techniques, tools, and resources used for analyzing textual requirements [11]. Similarly, Vierlboeck et al. reviewed NLP tools for extracting structure from natural-language requirements [3]. Therefore, NLP can be considered a foundational technique in AI-enabled RE.

4.2. Machine Learning and classification models

Machine Learning is used in RE to classify requirements, predict requirement-related patterns, prioritize requirements, and support decision-making. ML techniques are particularly useful when large datasets of requirements or stakeholder feedback are available. In AI-based prioritization studies, ML has been used to improve ranking, classification, clustering, and prediction accuracy [19], [41]. Murad et al. also used ML-based classification in an AI-driven framework for explicit and implicit requirement identification [18]. However, the literature also shows that ML-based approaches often require good-quality datasets and proper validation to produce reliable results [18], [42].

4.3. Deep Learning and transformer-based models

Deep learning approaches are increasingly used to capture deeper semantic relationships in requirement texts. Transformer-based models such as BERT are used because they can understand context better than traditional keyword-based techniques. For example, Radwan et al. used NLP, BERT embeddings, graph-based dependency modeling, clustering, and optimization for requirements prioritization in agile development [41]. Murad et al. also integrated BERT and BiLSTM for requirement classification and semantic understanding [18]. These studies show that transformer and deep learning models are useful where requirements are complex, ambiguous, or context-dependent.

4.4. Large Language Models and Generative AI

LLMs and GenAI are among the newest and most visible trends in AI-enabled RE. These models are used for requirement elicitation, requirement generation, specification writing, validation support, summarization, clarification, and analysis [10], [15], [40], [42]. Zadenoori et al. reviewed LLM applications in RE and found that recent studies mainly use GPT-based models and zero-shot or few-shot prompting for RE tasks [10]. Cheng et al. further showed that GenAI applications in RE are strongly associated with GPT-based models and prompt-based interaction, but also reported limitations such as hallucination, reproducibility, interpretability, and limited industrial adoption [42]. As such, LLMs and GenAI offer excellent automation potential, but they do need to be carefully validated and monitored by human users.

4.5. Prompt engineering and promptware engineering

Prompt engineering is gaining significance due to the reliance on prompt design in generating quality output from LLMs. Several techniques are being investigated for RE tasks: prompt engineering techniques include zero-shot prompting, few-shot prompting, chain-of-thought prompting, retrieval-augmented generation, constraint injection, and role-based prompting [9], [42]. Huang et al. summarized how to prompt meaningfully for RE and suggested a path forward for transitioning from ad-hoc prompting to more repeatable and practitioner friendly workflows [9]. Otherwise, Chen et al. have suggested that prompt development should be considered as a systematic software engineering process including prompt requirements, design, testing, debugging and evolution [1]. Thus, prompt engineering is not just an input style of a technical nature, but is emerging as a method to guide LLM-supported RE interventions.

4.6. Knowledge Graphs, ontologies, and semantic representation

Requirements, domain knowledge, relationships, dependencies and implicit knowledge are represented in a structured way with knowledge graphs and ontologies. The following methods are used to enhance the semantic traceability, consistency checking, impact analysis and requirement reasoning. Murad et al. employed knowledge graph for explicit and implicit requirements semantic enrichment, traceability and reasoning [18]. Belani et al. introduced the ontology-based RE for IoT supported well-being, aging and health systems [4]. Formalization and maintenance of the domain knowledge are also highlighted by the domain knowledge studies as being important in RE [8]. These techniques are particularly valuable when RE requires domain knowledge, explanation and reasoning based on relationships.

4.7. Optimization, recommender systems, and prioritization algorithms

Another crucial aspect from the literature selected is prioritization via AI. We use techniques like fuzzy logic, genetic algorithms, ant colony optimization, collaborative filtering/machine learning, recommender systems, matrix factorization, PageRank, Particle Swarm Optimization, clustering, dependency modeling to aid in requirement ranking and release planning [2], [19], [41]. For requirements prioritization, Felfernig explained the methods of constraint reasoning, optimization, utility based recommendation, matrix factorization, conflict detection, and model-based diagnosis using AI techniques [2]. In an attempt to enhance agile backlog prioritization, [41] applied NLP, BERT embeddings, graph-based dependency modeling, PageRank, UMAP, PSO, K-means, KNN and Random Forest algorithms in the development of their SAPC. These methods help alleviate manual workload and enable data-driven prioritisation decisions.

4.8. Multi-agent systems and collaborative AI frameworks

Multi-agent systems are emerging as a framework-based direction in AI-enabled RE. Instead of using one model for all tasks, multi-agent approaches divide RE work among specialized agents. [7] proposed MARE, a multi-agent collaboration framework in which LLM-based agents support elicitation, modeling, verification, and specification . This shows that agent-based AI can support more structured and collaborative RE workflows, especially when different RE tasks require different forms of reasoning, documentation, and verification.

4.9. Hybrid AI approaches

Some research indicates that future RE will likely depend on more than just one of these techniques, and utilize hybrid methods. Hybrid methods include NLP, ML, deep learning, knowledge graphs, optimization and human-in-the-loop validation. Murad et al. fused NLP, ML, deep learning, class imbalance solution, BERT, BiLSTM and KG in the same AI-based RE system [18]. At the same time, Cheng et al. highlighted that the current research on GenAI-for-RE still heavily depends on the usage of standalone GPT-based models and simple prompts, and more sophisticated hybrid architectures, retrieval-augmented approaches, and interactive strategies are still under-explored [42]. This is a significant future trajectory of the development of more reliable and context-aware RE solutions: hybrid AI.

Table 7. Major AI Techniques Used in Requirements Engineering

Key AI technique / approach	How it supports Requirements Engineering	Main RE activities supported	References
Natural Language Processing (NLP) and text mining	Processes natural-language requirements, extracts concepts, detects language issues, supports classification and traceability.	Elicitation, analysis, classification, traceability, validation	[3], [11]
Machine Learning and classification models	Learns from requirement datasets to classify, rank, predict, or organize requirements.	Analysis, classification, prioritization, management	[18], [19], [41], [42]
Deep Learning and transformer models	Captures contextual meaning in requirements using models such as BERT and BiLSTM.	Analysis, classification, ambiguity handling, prioritization	[18], [41]
Large Language Models and GenAI	Generates, analyzes, summarizes, validates, and refines requirement-related text.	Elicitation, specification, validation, analysis, documentation	[10], [15], [40], [42]

Prompt engineering / promptware engineering	Improves LLM output through structured prompts, examples, constraints, roles, and prompt lifecycle practices.	LLM-based elicitation, analysis, validation, specification	[1], [9], [42]
Knowledge Graphs and semantic representation	Represents requirements and domain relationships as connected knowledge structures for reasoning and traceability.	Analysis, traceability, impact analysis, implicit requirement discovery	[18], [4], [8]
Optimization and recommender techniques	Support requirement ranking, release planning, and decision-making using optimization, matrix factorization, recommendation, and dependency models.	Prioritization, release planning, management	[2], [19], [41]
Multi-agent AI frameworks	Uses multiple specialized AI agents to perform different RE tasks collaboratively.	Elicitation, modeling, verification, specification	[7]
Hybrid AI approaches	Combines NLP, ML, DL, GenAI, knowledge graphs, optimization, and human validation into integrated workflows.	End-to-end RE support, classification, traceability, prioritization, validation	[18], [42]

The literature selected reveals that AI-based Requirements Engineering is progressing toward intelligent, semantic, data-driven and generative AI support. Traditional NLP and ML techniques also are well represented as the requirements are often expressed in natural language, and NLP/ML techniques are applied to textual requirement analysis, defect detection and classification, requirement traceability and prioritization [11], [19]. Additional articles on the use of AI for prioritization indicate that the use of machine learning, fuzzy logic, genetic algorithms, ant colony optimization, recommendation methods and optimization techniques can assist in the requirement ranking and decision making process [2], [19], [41]. Recent research indicates a trend towards LLMs, GenAI, prompt engineering, transformer-based models, knowledge graphs, and multi-agent frameworks, particularly for LLM language-intensive RE activities like elicitation, specification, validation, analysis, documentation, and modeling [7] [9] [10] [18] [40] [42]. The main AI techniques, their application to RE and cited sources are summarized in Table 7. Prompt engineering research is aimed at bringing LLM-based RE tasks to be more systematic and more reproducible, and GenAI-based reviews indicate that the current applications of GenAI in RE still face some issues such as hallucination, reproducibility, interpretability, the lack of benchmarking and weak industrial adoption. Likewise, LLM reviews suggest that while LLMs have increasingly been used in RE tasks, a lot of times, they are evaluated in a controlled environment with limited application in real industrial workflows [10]. Thus, the answer to this research question is that AI-enabled RE currently uses NLP, ML, deep learning, transformers, LLMs, GenAI, prompt engineering, knowledge representation, optimization, clustering and multi-agent systems; and hybrid, explainable, and human-supervised approaches seem to be the most promising future path for the development of trustworthy RE solutions [18], [29], [42].

RQ3: Which specific Requirements Engineering activities are supported by AI-enabled solutions, and how are these solutions applied across different phases of the RE process?

AI-enabled solutions support several activities across the Requirements Engineering process because most RE artifacts are written in natural language and require analysis, interpretation, classification, validation, prioritization, and structured documentation. The reviewed studies show that NLP, ML, LLMs, GenAI, BERT-based models, knowledge graphs, optimization techniques, and multi-agent systems are being applied to support different RE phases, including elicitation, analysis, specification, validation, prioritization, traceability, and modeling [10], [11], [18]. However, AI support is not equally mature across all RE activities. Some phases, such as analysis, classification, prioritization, and NLP-based processing, have stronger research support, while full workflow integration and industrial RE management still require more practical validation [10], [11].

1. Requirements elicitation: AI-enabled solutions support requirements elicitation by helping analysts collect, interpret, and refine stakeholder needs. Data-driven elicitation uses digital sources such as user feedback, online reviews, social media, IoT data, and other dynamic data sources to identify requirement-related information [32]. ChatGPT and LLM-based approaches are also discussed for supporting elicitation by improving communication, generating requirement-related content, and helping capture user needs in software requirements engineering [40]. Therefore, AI is applied in elicitation to reduce manual effort, support stakeholder communication, and extract useful requirement information from both human and digital sources [32], [40].

2. Requirements analysis and classification: AI supports requirements analysis and classification through NLP, ML, deep learning, and semantic representation techniques. NLP-based RE studies support linguistic analysis tasks such as detecting language issues, identifying domain concepts, and supporting traceability in textual requirements [11]. AI-driven classification approaches also use TF-IDF, BERT, SMOTE/ADASYN, BiLSTM, and knowledge graphs to classify explicit and implicit requirements and represent them semantically [18]. Therefore, AI is applied in requirements analysis to identify ambiguity, incompleteness, requirement categories, domain concepts, and hidden requirement information [11], [18].

3. Requirements specification and documentation: AI-enabled solutions support requirements specification by generating, refining, and organizing requirement documents and related artifacts. LLM-based RE studies examine how large language models are used for RE tasks involving input artifacts, output artifacts, prompt strategies, and evaluation methods [10]. ChatGPT-based studies also discuss the use of generative models in software requirements engineering for producing and improving requirement-related content, while highlighting the importance of human feedback [40]. Multi-agent LLM-based RE frameworks also include specification as a dedicated task performed by specialized agents [7]. Therefore, AI is applied in specification and documentation to assist requirement writing, improve clarity, and structure requirement artifacts [7], [10], [40].

4. Requirements validation and verification: AI-enabled solutions support validation and verification by helping check requirements for correctness, consistency, completeness, and quality issues. Prompt engineering techniques are mapped to RE roles such as elicitation, validation, and traceability, showing that controlled prompting can support LLM-based validation tasks [9]. LLM-based RE reviews also identify validation as one of the RE activities supported by recent studies [10]. Multi-agent RE frameworks include verification as a core task, where agents collaborate to improve and check generated requirements artifacts [7]. Therefore, AI is applied in validation and verification to support requirement quality checking, but human review remains necessary before final acceptance [7], [9], [10].

5. Requirements prioritization and decision support: AI strongly supports requirements prioritization through ranking, optimization, recommendation, dependency analysis, and clustering. AI-based prioritization techniques include constraint reasoning, optimization, utility-based recommendation, matrix factorization, conflict detection, and model-based diagnosis [2]. Systematic review evidence also reports the use of genetic algorithms, fuzzy logic, ant colony optimization, and machine learning for AI-based requirements prioritization [19]. More recent prioritization models combine NLP, BERT embeddings, dependency graphs, PageRank, UMAP, PSO, clustering, and ML classifiers for agile backlog prioritization and clustering [41]. Therefore, AI is applied in prioritization to support requirement ranking, release planning, dependency analysis, backlog management, and decision-making [2], [19], [41].

6. Requirements traceability and semantic management: AI supports requirements traceability by identifying relationships among requirements, artifacts, domain concepts, and system elements. NLP-based RE studies include traceability-link recovery as an important task for textual requirements [11]. Prompt engineering research also connects prompting techniques with traceability-related RE roles [9]. Knowledge-graph-based approaches semantically structure classified requirements and support contextual traceability, semantic enrichment, and reasoning [18]. Therefore, AI is applied in traceability and semantic management to connect related requirements, support impact analysis, and improve understanding of requirement relationships [9], [11], [18].

7. Requirements modeling and model generation: AI-enabled solutions support requirements modeling by transforming natural language requirements into structured models, diagrams, or intermediate artifacts. Multi-agent LLM-based RE frameworks include modeling as one of the main RE tasks supported by specialized agents [7]. Automated RE frameworks for agile model-driven development use machine learning to extract essential components from natural language requirements, especially for class-diagram-related model generation [39]. Therefore, AI is applied in modeling to transform textual requirements into structured diagrams, models, and formalized artifacts [7], [39].

Table 8. AI-Supported Requirements Engineering Activities

Key RE Activity Supported by AI	How AI-Enabled Solutions Are Applied	Main AI Approaches Used	Supporting Citations
Requirements elicitation	AI helps collect, interpret, and refine stakeholder needs by extracting requirement-related information from digital sources and supporting stakeholder communication.	Data-driven elicitation, NLP, ChatGPT, LLMs	[32], [40]
Requirements analysis and classification	AI detects language issues, identifies domain concepts, classifies explicit and implicit requirements, and supports semantic requirement analysis.	NLP, ML, TF-IDF, BERT, BiLSTM, knowledge graphs	[11], [18]
Requirements specification and documentation	AI generates, refines, and organizes requirement documents and requirement-related artifacts.	LLMs, ChatGPT, multi-agent LLM specification	[7], [10], [40]
Requirements validation and verification	AI supports requirement validation, verification, and quality checking through prompt-based and agent-based workflows.	Prompt engineering, LLMs, multi-agent verification	[7], [9], [10]
Requirements prioritization and decision support	AI ranks, clusters, and prioritizes requirements for backlog management, dependency analysis, and release planning.	Optimization, ML, fuzzy logic, genetic algorithms, ACO, BERT, PageRank, PSO, clustering	[2], [19], [41]

Requirements traceability and semantic management	AI identifies links between requirements, artifacts, and domain concepts and supports semantic traceability and reasoning.	NLP, prompt engineering, knowledge graphs	[9], [11], [18]
Requirements modeling and model generation	AI transforms textual requirements into structured models, class-diagram elements, and intermediate modeling artifacts.	Multi-agent LLMs, ML-based model extraction	[7], [39]

There are numerous activities in Requirements Engineering that can be assisted by AI-enabled solutions such as elicitation, requirements analysis, requirements specification, requirements validation, requirements prioritization, traceability, and requirements modelling. The most promising results are found in NLP-based analysis and traceability [11], AI-based prioritization [2], [19], [41] and RE tools that utilize LLM support [10] and framework-based approaches for multi-agent and model-driven RE support [7], [39]. Table 8 provides a summary of the AI-supported RE activities, the applications, approaches and supporting citations. The results demonstrate that AI can be helpful in various stages of RE, with varying levels of development of the support offered by the AI system depending on the activity. Analysis, classification, and prioritization is technically more solid, whereas validation, management, and complete integration of the workflow has yet to be more thoroughly evaluated in an empirical and industrial context.

RQ4: What technical, methodological, ethical, and practical challenges limit the effective adoption of AI-enabled solutions in Requirements Engineering?

The literature reviewed indicates that there are several issues that hinder the reliable and practical use of a system in the field of Requirements Engineering (RE) that are associated with the use of AI. Technical, methodological, ethical and organizational challenges. Hallucination, inconsistent results, sensitivity to prompts, lack of interpretability, poor reproducibility, and lack of industrial use are reported as limitations of RE studies with LLM and GenAI [9, 40, 42]. Other reviews of NLP4RE and LLM4RE also reveal that most proposed solutions are still tested in academic or controlled environments rather than being a part of a fully-fledged industrial RE process [10] and [11]. Hence, it is important to have a more robust evaluation, explanation, security, supervision and industrial validation of the AI capabilities of RE before its full maturity.

Hallucination and inaccurate AI-generated requirements: One of the biggest hurdles in the LLM and GenAI based RE is the occurrence of hallucination, where LLM or GenAI generates requirement statements or explanations that may seem plausible, but are actually inaccurate or unsupported. Hallucination and incorrect answer are mentioned as risks to software requirements engineering in ChatGPT based research on RE [40]. Hallucination is also identified as one of the major issues that impact belief and consistency of RE research undertaken using GenAI [42]. Thus, incorrect requirements due to hallucinations can impact the correctness of the requirements and can mislead later design, development and validation decisions [40], [42].

Reproducibility, consistency, and prompt sensitivity: AI-enabled RE outputs, especially those generated by LLMs, may vary depending on prompt wording, examples, context, and model settings. Prompt engineering research explains that current LLMs involve uncertainty and lack of controllability, and that the absence of clear prompting guidance is a barrier to trustworthy RE implementation [9]. GenAI-based RE research also identifies reproducibility as one of the most frequently reported challenges [42]. Therefore, prompt sensitivity and inconsistent outputs make it difficult to reproduce, compare, and trust AI-generated RE artifacts [9], [42].

Lack of explainability, interpretability, and trust: Explainability is important because stakeholders and requirements engineers need to understand why a requirement was generated, classified, prioritized, or validated. RE4AI studies identify explainability as a major challenge for AI-based systems [29]. ChatGPT-supported RE research also discusses the need for explainability, transparency, and human involvement [40]. GenAI-based RE research identifies interpretability as a core challenge [42]. Therefore, lack of explainability reduces trust and makes it difficult to validate AI-supported RE decisions [29], [40], [42].

Limited industrial adoption and weak real-world validation: Many AI-enabled RE studies are evaluated in academic, controlled, or proof-of-concept settings instead of real industrial environments. NLP4RE research reports that only a small percentage of NLP4RE studies are assessed in industrial settings [11]. LLM4RE research also shows that many studies are evaluated in controlled environments, with limited industry use and limited integration into complex workflows [10]. GenAI-based RE research reports that industrial adoption remains limited and production-level integration is rare [42]. Therefore, limited industrial validation weakens confidence in the practical usefulness of AI-enabled RE solutions [10], [11], [42].

Data dependency, privacy, security, and governance concerns: AI-enabled RE depends on large, relevant, and high-quality data, but requirements data may include confidential stakeholder needs, business rules, domain constraints, or security-critical information. ChatGPT-based RE research discusses privacy and security concerns in software requirements engineering [40]. GenAI-based RE research also identifies security and ethics as governance-related concerns [42]. Therefore, privacy-aware data handling, secure processing, and governance mechanisms are necessary for responsible AI-enabled RE adoption [40], [42].

Bias, ethics, and fairness concerns: AI-enabled RE may reflect bias from training data, stakeholder representation, or generated outputs. RE4AI research discusses ethical implications and new quality requirements for AI-based systems [29]. ChatGPT-supported RE research also highlights ethical considerations in software requirements engineering [40]. GenAI-based RE research identifies bias and ethics as governance-related risks [42]. Therefore, bias mitigation, fairness-aware validation, and ethical review are necessary when using AI in RE [29], [40], [42].

Fragmented approaches and lack of integrated workflows: Many AI-enabled RE solutions focus on isolated tasks rather than full RE workflow integration. Prompt engineering research shows that prompting in RE is often treated as an ad-hoc implementation detail rather than a systematic design choice [9]. AI applicability research argues that although AI algorithms can support RE tasks, it is often unclear which algorithm can be applied to which RE process step [30]. GenAI-based RE research also identifies maturity gaps, fragmented benchmarking, and limited tool or dataset availability [42]. Therefore, fragmented approaches limit reuse, integration, benchmarking, and industry-ready adoption [9], [30], [42].

Need for human oversight and risk of overreliance: Requirements produced by AI can't be accepted without human inspection as they can be incomplete, incorrect, biased, or need to be adjusted based on the shared requirements of stakeholders. The use of ChatGPT for RE research highlights the need for human feedback and supervision in the process of requirements engineering in software development [40]. The use of GenAI for RE has also revealed that the issues of trust, consistency and governance are still relevant [42]. Hence, use of AI must be used to complement the work of requirements engineers, not to replace it and human experts must be responsible for validation and decision making [40], [42].

Table 9. Challenges Limiting AI-Enabled Requirements Engineering Adoption

Key Challenge	Explanation	Impact on Requirements Engineering	Supporting Citations
Hallucination and inaccurate AI-generated requirements	LLMs and GenAI may generate incorrect or unsupported requirement-related content.	Can create false requirements and mislead design, development, and validation decisions.	[40], [42]
Reproducibility, consistency, and prompt sensitivity	AI outputs may vary across runs and depend strongly on	Makes RE outputs difficult to reproduce, compare, and trust.	[9], [42]

	prompt wording, context, and model settings.		
Lack of explainability, interpretability, and trust	AI systems may not clearly explain why a requirement was generated, classified, prioritized, or validated.	Reduces stakeholder confidence and makes validation difficult.	[29], [40], [42]
Limited industrial adoption and weak real-world validation	Many AI-enabled RE studies are tested in academic or controlled environments.	Limits evidence of practical usefulness in real RE workflows.	[10], [11], [42]
Data dependency, privacy, security, and governance concerns	AI-based RE requires quality data, while requirements data may be sensitive or restricted.	Creates barriers for industrial, confidential, or safety-critical RE use.	[40], [42]
Bias, ethics, and fairness concerns	AI outputs may reflect biased data or raise ethical and fairness concerns.	Can lead to unfair, incomplete, or ethically weak requirements.	[29], [40], [42]
Fragmented approaches and lack of integrated workflows	Existing AI solutions often address isolated tasks, ad-hoc prompting, or unclear process-step mapping.	Limits reuse, integration, benchmarking, and practical adoption.	[9], [30], [42]
Need for human oversight and risk of overreliance	AI outputs require human review, feedback, and validation before acceptance.	Prevents blind acceptance of inaccurate or incomplete RE artifacts.	[40], [42]

To wrap up, the challenges facing the use of AI in Requirements Engineering are: hallucination, non-uniform responses, sensitivity to prompts, poor reproducibility, lack of explanation, privacy and security concerns, ethical concerns, disintegration, lack of industrial validation, and human supervision. The challenges are highly reported from the LLM, GenAI, ChatGPT and NLP4RE studies [9], [10], [11], [40], [42]. The key challenges, along with explanations and impacts are summarized in Table 9. There is some evidence suggesting that this is not an entirely stand-alone solution for requirements engineers using AI to assist with RE. Rather, solutions for the future will need to emphasize explainable outputs, reproducible workflows, secure data handling, more robust industry testing, and human-in-the-loop testing.

RQ5: What AI-enabled frameworks, models, tools, or architectures have been proposed for Requirements Engineering, and how do they contribute to the development of intelligent, automated, and trustworthy RE practices?

The literature selected consists of several frameworks, models, tools and architectures that are designed to make Requirements Engineering more intelligent, automatic, semantic and trustworthy. These solutions come in various forms. Some of them deal with multi-agent LLM collaboration, some deal with explicit and implicit requirement classification, some with agile prioritization, some with transforming natural language requirements into models, and others with ontology-based RE, AI process-step mapping or prompt engineering. The most relevant contributions are based on the concept of a framework such as multi-agent RE support [7], explicit and implicit requirement classification with knowledge representation [18], the development of a roadmap for RE research for the domain of agile model-driven development with GenAI [42], smart agile prioritization and clustering [41], automated RE for agile model-driven development [39], ontology-based RE [4] and the development of a taxonomy of prompts and a roadmap for prompt engineering research in RE [9].

A multi-agent collaboration framework for Requirements Engineering divides the RE process into elicitation, modeling, verification, and specification, and assigns these tasks to specialized LLM-based agents [7]. The framework also uses a shared workspace where agents exchange intermediate requirements artifacts [7]. This contributes to intelligent and automated RE by supporting role-based collaboration across multiple RE tasks [7].

An intuitive framework for Information Collection in RE using explicit and implicit information adopted by AI combines NLP, ML, TF-IDF, BERT, SMOTE/ADASYN, BiLSTM and Knowledge Graphs to represent the requirements, classify and extract them [18]. This helps with the classification of requirements, their semantic enrichment, their traceability and reasoning, which are key to intelligent RE [18].

In [42] a systematic review of GenAI for Requirements Engineering is presented, which categorizes the research trends, methodologies, challenges, evaluation gaps, tools/datasets, industrial adoption and future directions of the research on GenAI-for-RE. This helps raise awareness of gaps in maturity and the importance of robust assessment, oversight and industrial scale standardization in trustworthy AI-driven RE [42].

Smart Agile Prioritization and Clustering is an AI-driven model for requirements prioritization in agile software development [41]. It uses NLP, BERT embeddings, graph-based dependency modeling, PageRank, UMAP, Particle Swarm Optimization, clustering, and ML classifiers [41]. This contributes to automated RE by supporting backlog prioritization, dependency analysis, requirement clustering, and data-driven decision-making [41].

An automated requirements engineering framework for agile model-driven development uses machine learning models to extract important components from natural language requirements, especially for class diagram generation [39]. This contributes to automated RE by helping transform textual requirements into structured modeling artifacts [39].

An ontology-based Requirements Engineering approach for IoT-supported well-being, aging, and health systems extends the SAREF4EHAW ontology to represent domain concepts, system requirements, use cases, and sensor-related semantics [4]. This contributes to semantic and trustworthy RE by making requirement knowledge more structured, formal, and machine-interpretable [4].

A framework for identifying possible AI applications in Requirements Engineering processes addresses the problem that, although AI algorithms can support RE tasks, it is often unclear which AI algorithm can be applied to which process step [30]. The framework provides standardized RE process steps from a data-processing perspective, helping organizations identify where AI algorithms may be applied [30].

A roadmap-oriented systematic review and taxonomy for prompt engineering in Requirements Engineering links prompt engineering techniques such as few-shot prompting, chain-of-thought, retrieval-augmented generation, constraint injection, and multi-role dialogue with RE roles such as elicitation, validation, and traceability [9]. This contributes to trustworthy LLM-based RE by moving prompt use from ad-hoc experimentation toward more systematic and reproducible workflows [9].

Table 10. AI-Enabled Frameworks, Models, Tools, and Architectures for Requirements

Framework / Model / Architecture	Main Contribution to RE	How It Supports Intelligent, Automated, or Trustworthy RE	Supporting Citations
MARE multi-agent collaboration framework	Divides RE into elicitation, modeling, verification, and specification using LLM-based agents.	Supports role-based, collaborative, and structured LLM-assisted RE.	[7]
AI-driven explicit and implicit requirement classification and knowledge representation framework	Combines NLP, ML, TF-IDF, BERT, SMOTE/ADASYN, BiLSTM, and knowledge graphs.	Improves requirement extraction, classification, semantic enrichment, traceability, and reasoning.	[18]

GenAI-based RE systematic framework and research roadmap	Organizes GenAI-for-RE trends, methodologies, challenges, evaluation gaps, tools/datasets, and future directions.	Supports maturity analysis and identifies trustworthy GenAI adoption barriers.	[42]
SAPC smart agile prioritization and clustering model	Uses NLP, BERT, dependency graphs, PageRank, UMAP, PSO, clustering, and ML classifiers.	Automates backlog prioritization, clustering, dependency analysis, and decision support.	[41]
Automated RE framework for agile model-driven development	Uses ML to extract components from natural language requirements for model generation.	Supports formalization of textual requirements into structured modeling artifacts.	[39]
Ontology-based RE approach	Uses ontology extension to structure requirements, use cases, and domain semantics.	Improves semantic clarity, domain alignment, and formal representation of requirement knowledge.	[4]
AI applicability framework for RE process steps	Provides standardized process steps to identify where AI algorithms can support RE.	Bridges the gap between AI capabilities and practical RE process application.	[30]
Prompt engineering taxonomy and roadmap for RE	Links prompt engineering techniques with RE tasks and proposes a roadmap.	Supports systematic, reproducible, and controlled LLM-based RE workflows.	[9]

The literature selected has demonstrated that the use of AI in RE is no longer limited to single techniques, but is increasingly based on structured frameworks, models and architectures. Multi-agent LLM support is used for collaboration on elicitation, modeling, verification, and specification [7] and knowledge-graph based AI framework is used for handling explicit and implicit requirements by combining NLP, ML, deep learning, and semantic representation [18]. There are examples of AI-driven prioritization models that facilitate agile backlog management with dependency aware computational techniques [41] and automated model driven RE framework that assists in capturing the textual requirements as structured artifacts [39]. Semantic representation, process integration, and reproducible LLM-based workflows are also facilitated by ontology-based approaches [4] and AI applicability frameworks [9] and prompt engineering roadmaps [30]. Such are the major frameworks, models, tools and architectures summarized in Table 10. In summary, the results indicate that AI-powered RE is progressing towards more holistic and intelligent assistance, yet the widespread industrial validation, robust assessments, and supervision are still required to develop solutions to maturity.

4. Discussion

The synthesis of the five research questions reveals a shift towards more intelligent, semantic, generative and framework-based assistance for Requirements Engineering (RE) using AI. From the 43 studies selected, it seems that the research is spread out over various publication venues such as the software engineering (SE) journals, AI related journals, Requirements Engineering (RE) conferences, workshop proceedings, book chapters, outputs of arXiv/CoRR. The geographical analysis and publication indicate a high level of interest in the topic in Europe, Asia and North America, with other geographical areas being less well-represented. This distribution indicates that AI powered RE is emerging as a worldwide research field, but also that the attention paid to research contributions varies between regions as seen in Tables 4, 5 and 6.

The results of RQ2 reveal that many techniques are currently used for supporting AI-enabled RE, such as NLP, ML, deep learning, transformer-based models, LLMs, GenAI, and prompt engineering, as well as knowledge graphs, ontology-based techniques, optimization algorithms, clustering, and multi-agent systems. NLP and ML are still central for requirements as they are frequently expressed and written in natural language and need to be classified, detected for ambiguity, traced and interpreted semantically [11], [19]. Meanwhile, recent research indicates a significant trend towards the use of LLMs and GenAI for language-rich RE activities like elicitation, specification, validation, analysis, documentation, and modelling [10], [40], [42]. These newer techniques are yet to be fully developed as they are still plagued by several problems like hallucination, sensitivity of prompts, lack of benchmarking and low adoption by industry [9], [42]. Thus, the results indicate that RE using AI is technically complex, and must be carefully selected, evaluated, and supervised by humans.

In the results of RQ3, it can be seen that AI-assisted solutions contribute to various RE activities, such as elicitation, analysis, specification, validation, prioritization, traceability and modeling. Data driven elicitation approaches are used for data mining the information related to requirements from the user feedback [32] and LLM-based approaches are used to support communication and the production of requirement contents [40]. NLP, ML, BERT, BiLSTM and knowledge-graph-based methods greatly assist in requirements analysis and classification [11, 18]. Priority is another well-developed sub-area that relies on techniques such as optimization and genetic algorithms, fuzzy logic, ant colony optimization, machine learning, BERT embeddings, dependency modeling, PageRank, PSO and clustering for priority ranking and decision making, as part of AI-based priority [2], [19], [41]. The results suggest that AI can be applied in various stages of the RE process, with varying levels of maturity for certain activities. Analysis, classification, and prioritization are more well-founded technically, while the remaining aspects of the workflow – validation, requirements management, and complete workflow integration – still need to be better evaluated in practice and industry.

RQ4 findings reveal that there are a number of technical, methodological, ethical, and practical challenges to the use of AI-based RE. Hallucination, inaccurate outputs, reproducibility issues, prompt sensitivity, limited interpretability and lack of controllability are the drawbacks of LLM and GenAI-based RE solutions [9], [40], [42]. The challenges are important because the requirements have direct impact on software design, implementation, testing and the satisfaction of the stakeholders. When AI generated requirements are wrong or unsupported, they can result in suboptimal decisions for the system. Additionally, there are numerous studies that investigate AI applications for RE that are not integrated into industrial applications or workflows, nor have been validated in real world scenarios [10], [11], [42]. Other concerns that are also relevant are privacy and security; requirement documents might include confidential business rules and/or stakeholder requirements as well as sensitive system constraints [29], [40], [42]. The results demonstrate that the use of AI in RE is not a standalone approach that can completely replace the role of the requirements engineer. Rather, it should be used alongside human experts to help with decision making and automate certain processes, while the human will also be responsible for validation, ethics and acceptance.

Based on RQ5 results, the focus on the field is gradually moving from the use of individual AI techniques to structured frameworks, models, tools and architectures. Multi-agent LLM-based frameworks can be used for collaborative RE activities like elicitation, modelling, verification and specification [7]. The knowledge-graph based frameworks involve in NLP, ML, deep learning and semantic representation in order to facilitate the explicit and implicit requirement classification and contextual traceability [18]. Models driven by AI can be used for prioritizing the backlog in agile development and to inform decision making based on dependencies [41], and automated model-driven RE frameworks can be used to construct modeling artifacts from natural language requirements [39]. The use of ontology-based approaches helps to represent and formalize the requirement [4] and promote more systematic and reproducible LLM-based RE workflows [9] through the use of prompt engineering roadmaps. The framework-based contributions suggest that AI-based RE is progressing toward the more integrated and intelligent support but more industrial validation and evaluation methods are required.

In summary, there are three main changes that are suggested in the discussion regarding the role of AI in Requirements Engineering. Summarizing, the three key changes in the use of AI for Requirements Engineering are highlighted in the discussion. The first one is moving away from manual RE support to intelligent automation whereby AI helps analysts in classification, prioritization, specification and validation [2] [11] [19]. Second, it transitions from text processing to semantic and generative understanding, with the support of knowledge graphs, ontologies, LLMs and GenAI, which enables it to better process and interpret requirement artifacts and produce them. Second, it moves from text processing to semantic and generative understanding, supported by knowledge graphs, ontologies, LLMs and GenAI, allowing for better interpretation and generation of requirement artifacts. Third, it is shifting from standalone tools to frameworks that integrate several tools into a unified system, such as multi-agent systems, prompt engineering roadmaps, automated RE frameworks, and models of AI applicability, which try to link the AI capabilities with real RE workflows [7], [9], [30], [39]. Although these progressions have been made, for sustainable adoption, it is important that systems be explainable, reproducible, treat the data securely, be governed in an ethical manner, be evaluated in industry and have human validation in the loop. It is important to note that future research should aim for creating trustworthy, explainable, and industry-ready RE solutions, which should be able to assist with the entire RE lifecycle, instead of just specific tasks.

5. Taxonomy

This study employed a systematic structure as presented in the taxonomy diagram (Figure 4) to review the area of AI-enabled Requirements Engineering (RE) from a systematic perspective. It breaks the entire review process down into three stages: planning the review, carrying out the review and documenting the review. During the planning phase, research questions are constructed, the review protocol is drawn up and the protocol is checked with the help of an expert or supervisor. The conducting phase will involve searching for relevant studies in selected academic databases, the use of inclusion and exclusion criteria and data extraction from the final selected studies. In this study, 43 papers are selected as data extraction, to make a review result on the selected papers. Lastly, the documenting phase consists of RQ-wise analysis, discussion of findings, validation of results, implications and future directions. This taxonomy is intended to give an overall structure and clarity to the way the SLR process has been designed and implemented.

Overall, the taxonomy diagram demonstrates that the review process was carried out in a structured and systematic way, with transparency. The diagram shows the process in steps to identify the different components of the study and how they all help ensure reliability. The methodological framework of the review is strengthened by the use of defined research questions, a clear review protocol, database-based identification of the studies and inclusion and exclusion criteria. Defined research questions, a clear review protocol, database based study identification and procedures of inclusion and exclusion of papers and data extraction from 43 papers strengthens the methodological foundation of the review. The taxonomy in the study also confirms that the study is not just a gathering of papers, but includes a discussion and analysis of the papers by RQ to get meaningful results. This taxonomy will thus contribute to the credibility of the review and a better understanding of how the study systematically investigates solutions in Requirements Engineering using AI.

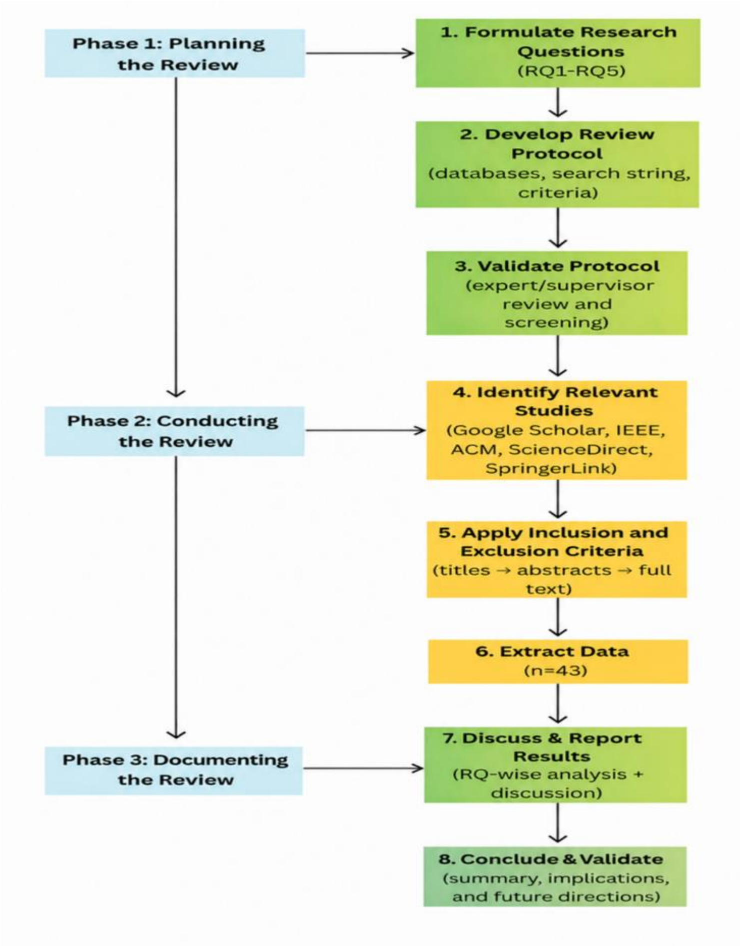

Figure 4. Taxonomy

6. Limitations

The results from this systematic literature review offer a structured overview of the solutions that are supported by AI in RE, but are limited by the selected corpus of 43 studies. These studies represent significant work in the areas of NLP4RE, LLM4RE, GenAI for RE, prompt engineering, AI-based prioritization, knowledge graphs, ontology-based RE, automated RE frameworks, and RE for AI-based systems; however, the field is developing very rapidly. New research on LLM, GenAI, and prompt-based RE may emerge beyond the review period that could add new tools, frameworks, datasets, and/or evaluation methodology that are not presented in this review.

The papers reviewed are of different type, scope and maturity in research. Some studies are systematic reviews or mapping studies, others are experimental studies, conceptual frameworks, tool-based papers, or early stage research papers. This difference makes it challenging to compare all papers at the same level. The research base of NLP-based RE and AI-based prioritization is more extensive than that of LLM-based RE, GenAI-based RE, and prompt engineering for RE, which are still in the early stages and needs more empirical evidence. Hence, the results presented in this review should be seen as an overview of the research trends, and not as an end-of-the-day verdict on the effectiveness of each of the different AI-based RE methods.

While there are many AI-based RE approaches being tested in academic or controlled or limited experimental settings, very few have been tested in industrial settings. For this reason, though AI techniques are promising to be effective for elicitation, analysis, specification, validation, prioritization, traceability, and modeling, there still needs to be more evidence of their effectiveness in large-scale industrial projects. The performance of these solutions can be influenced by real-world factors like stakeholder diversity and evolving needs, organizational limitations, data privacy, tool integration, and project complexity.

A quantitative meta-analysis was not possible due to different datasets, methods, evaluation metrics, tools, domains and reporting styles used in the selected studies. Some papers have accuracy/precision/recall or F1 score while others have frameworks, taxonomies, roadmaps, conceptual models, or qualitative findings. It is difficult to make statistical comparisons directly because of this methodological diversity. Hence, a thematic synthesis and a RQ-wise analysis of all the studies was used instead of a numerical comparison.

One significant challenge mentioned in the literature is the lack of reliability of the AI-generated RE outputs. While LLM and GenAI can aid in requirement generation, analysis, documentation and validation, they can also hallucinate, be inconsistent, biased, or hard to explain. The results of REs using LLM are also sensitive to prompts and reproducible. For this reason, there is a need to view AI-driven RE as a complement to, rather than a substitute for, human RE professionals. Even after human validation and stakeholder review, the correctness, completeness and need of the real project are still required.

This review is also constrained by the information that is explicitly provided in reviewed papers and matrix table. If a study was not clearly stated, any assumption was not included. This helps enhance the credibility of the review, but also implies that some items might not be reported fully if they were not reported clearly in the original papers.

7. Conclusion

The systematic literature review titled "Towards Intelligent Requirements Engineering: A Systematic Review of AI-Enabled Solutions" reviewed the current status of solutions that enable the use of AI in the field of Requirements Engineering. The review, based on the synthesis of 43 selected studies, demonstrates that AI support for RE is evolving from the most basic forms of automation toward the more intelligent, semantic, data-driven and generative forms of support. Various techniques are being used with different RE activities to help them, including NLP, ML, deep learning, transformer-based models, LLMs, GenAI, prompt engineering, knowledge graphs, ontologies, optimization algorithms, clustering and multi-agent systems.

The results revealed that NLP and ML are widely used techniques as requirements are commonly expressed in natural language, and there are issues of requirements classification, quality checking, semantic analysis, and requirement traceability support. Another area of promising research is prioritization using AI, where machine learning, fuzzy logic, genetic algorithm, ant colony optimization, optimization methods, BERT embeddings, PageRank, PSO and clustering techniques are employed to aid requirement prioritization and decision-making. These more recent studies highlight the growing focus on language-intensive RE activities, including elicitation, specification, validation, analysis, documentation, and modelling, and how these are being related to LLMs and GenAI.

The review also identified AI-enabled solutions to aid in several activities of RE, such as elicitation, analysis, classification, specification, documentation, validation, verification, prioritization, traceability, semantic management, and modelling. Elucidations can be obtained from digital sources using data-driven elicitation, analysis and classification with NLP and ML, and specification, validation and documentation with LLM-based techniques. Agile backlog management and release planning enabled by the AI-based prioritization, and semantic representation and traceability of knowledge graphs and ontologies.

Another significant discovery is that structured frameworks, models, tools and architectures are gaining in supporting the use of AI for RE. Multi-agent LLM frameworks are used for collaborative RE activities like elicitation, modeling, verification, and specification. The Knowledge-graph based frameworks include NLP, ML, deep learning, and explicit and implicit requirement handling using semantic representation. Automated RE frameworks can help in the model-driven development by converting the natural language requirements into structured modeling artifacts. Prompt engineering roadmaps are designed to render LLM-based RE more systematic and reproducible and AI applicability frameworks are used to determine the application of AI algorithms in the various steps of the RE process.

However, a significant number of barriers and challenges, including hallucination, inconsistent outputs, prompt sensitivity, weak reproducibility, limited interpretability, and trust issues, are key challenges for the adoption of AI-based RE-enabled solutions, as noted in the review. Issues of privacy and security, as well as bias, ethics and governance continue to be relevant as requirements can include sensitive stakeholder needs, business rules and constraints on the system. Moreover, there is a lack of industrial validation, and production-level integration is still a challenge.

In conclusion, this review demonstrates that AI holds significant promise for enhancing the RE process through the automation of tasks, facilitation of analysis, aids to prioritization, documentation, semantic representation, and solidifies decision making. Meanwhile, explainability, reproducibility, ethical governance, secure data handling, reliable evaluation, industrial validation and human-in-the-loop supervision are all necessary for successful adoption. Therefore, using AI in RE should be considered as an intelligent assistance method to enhance the work of requirements engineers, not as a replacement.

8. Future Directions

Moving forward, the adoption of AI-powered RE solutions in industry should be investigated. Current studies are carried out in an academic or controlled environment and future studies should explore testing of AI RE tools in real software organizations, agile teams, large-scale projects, and safety-critical domains. This would help to evaluate if AI-powered RE methods are still applicable to actual stakeholder communication, evolving needs, partial knowledge or organizational restrictions.

Standardized data, benchmarks and evaluation metrics are also needed. The studies that are currently being conducted involve various datasets, tasks, models and measures of performance, making it difficult to compare them. There would be a greater level of reliability and comparability in future research if there were shared benchmarks for elicitation, classification, ambiguity detection, prioritization, traceability, validation, and specification.

Improvements are needed in the future to make AI-based RE tools more explainable and interpretable. Requirements engineers should document the "how/why" of the creation, classification, prioritisation and validation of an AI system. Trust and stakeholder acceptance can be enhanced through the use of explainable outputs, confidence scores, evidence links and traceability paths.

There is a need to further develop HITL RE frameworks. While LLM and GenAI can assist with RE, it is important that the human expert continue to be engaged in reviewing, correcting, approving and making final decisions as LLM-generated outputs can be inaccurate or hallucinated. Future systems should enable collaboration of AI tools, requirements engineers, domain experts and stakeholders.

Also, future research should focus on creating new prompt engineering techniques for RE, such as reusable prompt templates, prompt repositories, domain-specific prompting techniques, and prompt evaluation techniques, to increase RE's reproducibility and decrease its reliance on ad-hoc LLM prompt usage.

Another direction that holds promise is the development of hybrid approaches that integrate NLP, ML, LLMs, GenAI, knowledge graphs, ontologies, optimization techniques and human oversight. These hybrid systems can offer more reliable, explainable and context-sensitive assistance to all of the Requirements Engineering Lifecycle.

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