CognitivaTech: Ingeniería de Software Inteligente y Sistemas Adaptativos. 2026; 3(1):52
doi: 10.63688/cognitivatech.v3.i1.52

ORIGINAL

AI assisted requirements engineering for system development

Ingeniería de requisitos asistida por inteligencia artificial para el desarrollo de sistemas

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Submitted: 03-01-2026 | Revised: 27-02-2026 | Accepted: 29-04-2026 | Published: 31-03-2026

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ABSTRACT

Objective: To analyze the relationship between AI-assisted requirements engineering and the development of intelligent systems, considering its contribution to the elicitation, drafting, analysis, classification, validation and traceability of software requirements. Methodology: A quantitative, non-experimental, cross-sectional and descriptive-correlational research was carried out with a sample of 143 students, teachers and professionals linked to software development, information technologies, functional analysis and systems engineering. The information was collected using a 24-item questionnaire with a Likert-type scale, validated by specialists and with a Cronbach's alpha coefficient of 0.87. For the analysis, descriptive statistics and Spearman's correlation coefficient were applied. Results: A favorable perception was identified about the use of artificial intelligence in requirements engineering activities. The main contributions were observed in the drafting, classification, clarity, coherence, precision and reduction of ambiguities of the requirements. The correlational analysis evidenced a positive and statistically significant relationship between AI-assisted requirements engineering and the development of intelligent systems, with the quality of requirements being highlighted as the dimension with the greatest relationship. Limitations associated with bias, misinterpretation, technological dependence, and lack of contextualization were also recognized. Conclusions: Artificial intelligence can strengthen the efficiency and quality of requirements engineering, facilitating the development of clearer, more organized and verifiable specifications.

Keywords: artificial intelligence, requirements engineering, intelligent systems, software requirements, software development.

RESUMEN

Objetivo: Analizar la relación entre la ingeniería de requisitos asistida por inteligencia artificial y el desarrollo de sistemas inteligentes, considerando su aporte en la elicitación, redacción, análisis, clasificación, validación y trazabilidad de los requisitos de software. Metodología: Se desarrolló una investigación cuantitativa, no experimental, transversal y descriptivo-correlacional, con una muestra de 143 estudiantes, docentes y profesionales vinculados con el desarrollo de software, las tecnologías de la información, el análisis funcional y la ingeniería de sistemas. La información se recopiló mediante un cuestionario de 24 ítems con escala tipo Likert, validado por especialistas y con un coeficiente alfa de Cronbach de 0,87. Para el análisis se aplicaron estadísticos descriptivos y el coeficiente de correlación de Spearman. Resultados: Se identificó una percepción favorable sobre el uso de la inteligencia artificial en las actividades de ingeniería de requisitos. Los principales aportes se observaron en la redacción, clasificación, claridad, coherencia, precisión y reducción de ambigüedades de los requisitos. El análisis correlacional evidenció una relación positiva y estadísticamente significativa entre la ingeniería de requisitos asistida por inteligencia artificial y el desarrollo de sistemas inteligentes, destacándose la calidad de los requisitos como la dimensión con mayor relación. También se reconocieron limitaciones asociadas con sesgos, errores de interpretación, dependencia tecnológica y falta de contextualización. Conclusiones: La inteligencia artificial puede fortalecer la eficiencia y la calidad de la ingeniería de requisitos, facilitando la elaboración de especificaciones más claras, organizadas y verificables.

Palabras clave: inteligencia artificial, ingeniería de requisitos, sistemas inteligentes, requisitos de software, desarrollo de software.

INTRODUCTION

Requirements engineering is among the most decisive phases in the software development life cycle, since it allows identifying, analyzing, documenting, validating, and managing the needs that guide the construction of a system. In the case of intelligent systems, this phase becomes more complex, because it is necessary not only to define operational functions but also to establish conditions associated with machine learning, autonomy, explainability, security, ethics, data quality, and user interaction. For this reason, the integration of artificial intelligence into requirements engineering represents a relevant alternative to strengthen the precision, traceability, and quality of specifications used in advanced technological projects.

Artificial intelligence-based systems exhibit characteristics that differentiate them from traditional systems, mainly because their behavior may depend on data, predictive models, uncertainty levels, and adaptation processes. Ahmad et al. (1) point out that requirements engineering for AI systems demands more specialized practices, capable of addressing dynamic conditions, performance criteria, and risks inherent to this type of solution. In addition, Habiba et al. (2) argue that the maturity of requirements engineering in AI-based systems still presents methodological limitations, especially in the definition of verifiable, explainable requirements aligned with the context of use.

From this perspective, artificial intelligence should not only be understood as the final result of an intelligent system, but also as a support resource to improve software engineering activities. Ahmad et al. (3) propose a requirements engineering framework oriented toward human-centered artificial intelligence systems, highlighting the need to incorporate technical, social, and ethical aspects from the early stages of development. However, gaps remain in the way teams formulate requirements for this type of system, especially when seeking to translate human needs into clear, evaluable, and verifiable technical specifications (4).

Among the activities where artificial intelligence can provide the most value is requirements elicitation. This process often relies on interviews, meetings, questionnaires, document analysis, and user observation; however, these techniques can generate incomplete information when stakeholders do not clearly express their needs or when there are multiple interests within the project. Akram et al. (5) explain that recommendation systems can support the elicitation of requirements by suggesting functionalities or features based on previous experiences, user preferences, and patterns identified in similar projects. In turn, automatic extraction from user-generated content enables leveraging comments, reviews, reports, forums, and other unstructured texts to discover real system needs (6).

Generative artificial intelligence has also opened new possibilities to assist requirements engineering, especially through the use of large language models. These models can support the writing of user stories, the improvement of specifications, the detection of inconsistencies, the reformulation of ambiguous requirements, and the initial generation of functional scenarios. Arora et al. (7) argue that generative models can strengthen different requirements engineering tasks, as long as there is human supervision and contextual validation. Along the same lines, Cheng et al. (8) warn that their application also entails risks related to hallucinations, interpretation errors, and excessive dependence on automated responses.

Natural language processing is another relevant technology for artificial intelligence-assisted requirements engineering. Most requirements are written in natural language because it facilitates communication among users, analysts, and developers; however, it can also generate ambiguities, duplications, contradictions, or lack of precision. Necula et al. (9) indicate that automatic language processing enables analyzing textual documents, identifying relevant information, classifying requirements, and detecting problems in software specifications. This capability is especially useful in intelligent systems projects, where an incorrect interpretation can affect the model design, data selection, and user acceptance of the system.

The classification of functional and non-functional requirements has also been strengthened through machine learning techniques. Functional requirements describe what the system should do, while non-functional requirements establish quality conditions such as security, performance, usability, maintainability, privacy, and reliability. In this area, machine learning algorithms can support the identification and classification of non-functional requirements, reducing the manual effort of development teams. Furthermore, artificial intelligence techniques applied to requirements classification enable organizing large volumes of information and improving the management of specifications in complex projects (10,11).

The use of machine learning in requirements engineering has also been related to tasks of analysis, prioritization, recommendation, and inconsistency detection.

Li et al. (12) point out that these techniques can contribute to different activities of the requirements process, although their effectiveness depends on the quality of the data, the training of the model, and the interpretation carried out by professionals. For their part, Umar and Lano (13) highlight that advances in automated support have made it possible to improve the extraction, analysis, validation, and management of requirements, although there are still challenges linked to the integration of these tools in real development environments and to user trust in the generated results.

Another important aspect in the development of intelligent systems is the early incorporation of privacy and security requirements. These systems often work with sensitive data, automated processes, and models that can influence decision-making, so it is necessary to define clear conditions from the outset to protect information and reduce risks. Casillo et al. (14) point out that the automatic identification of privacy and security requirements can strengthen the design of more reliable systems, since it allows these elements to be considered before the product reaches advanced implementation phases. This perspective is fundamental because errors in the definition of requirements can lead to vulnerabilities, biases, regulatory compliance failures, or loss of user trust.

Overall, recent studies show that artificial intelligence can support requirements engineering in activities such as elicitation, classification, analysis, validation, traceability, and ambiguity detection. However, it is also recognized that its application must remain under human supervision, because models can generate imprecise results, rely on incomplete data, or assume conditions that do not correspond to the project context. Therefore, AI should not replace the requirements analyst, but rather act as an assistance tool that improves the quality of specifications and facilitates decision-making during the development of intelligent systems.

Based on the foregoing, the present study aims to analyze the relationship between artificial intelligence-assisted requirements engineering and the development of intelligent systems, considering its contribution to the elicitation, analysis, classification, validation, and traceability of software requirements. To this end, one quantitative investigation is proposed, with a descriptive-correlational scope, using a sample of 143 participants linked to software development, information technology, functional analysis, teaching, and systems engineering. This approach will allow identifying the participants' perception of the use of artificial intelligence in requirements engineering and its impact on the quality of intelligent systems development.

METHODS

The research was conducted under a quantitative approach, as it sought to measure participants' perception of the use of artificial intelligence in requirements engineering and its relationship with the development of intelligent systems. This approach allowed information to be organized through numerical data, apply descriptive statistical procedures, and establish associations among the studied dimensions. The scope was descriptive-correlational, since first the level of AI usage in requirements activities was characterized, and then the relationship between such technological assistance and the perceived quality in the development of intelligent systems was analyzed.

The design was non-experimental and cross-sectional. It was non-experimental because no variable was manipulated nor was a controlled intervention applied, but rather information was collected from the experiences and perceptions of the participants. It was cross-sectional because the data were collected at a single point in time, allowing a specific view of the current state of the use of artificial intelligence in requirements engineering processes.

The population was made up of students, teachers, and professionals related to software development, information technologies, functional analysis, systems engineering, and requirements engineering. The sample consisted of 143 participants, selected through non-probability convenience sampling, considering as the main criterion the direct or indirect relationship of the participants with processes of analysis, design, documentation, or development of computer systems.

The technique used was the survey, and the instrument was a structured questionnaire with a 5-level Likert scale: 1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree, and 5 = strongly agree. The questionnaire consisted of 24 items distributed across 4 dimensions: use of artificial intelligence in requirements engineering, quality of requirements, development of intelligent systems, and limitations of the use of IA. This structure allowed for the evaluation of both the contributions of AI and the potential risks associated with its application in requirements processes.

The first dimension, use of artificial intelligence in requirements engineering, evaluated the application of intelligent tools in tasks such as elicitation, writing, analysis, classification, prioritization, validation, and traceability of requirements. The second dimension, quality of requirements, allowed assessing the clarity, completeness, coherence, precision, and reduction of ambiguities in specifications generated or reviewed with AI support. The third dimension, development of intelligent systems, analyzed the perception of the contribution of AI-assisted requirements in the design of solutions based on automation, machine learning, data analysis, or intelligent decision-making. Finally, the fourth dimension, limitations of AI use, considered aspects such as technological dependence, errors in generated responses, biases, lack of contextualization, and the need for human validation.

Table 1. Sample distribution

Participant Profile	Frequency	Percentage
Students of software, systems, or information technology degree programs	76	53,1 %
Developers or programmers	38	26,6 %
Requirements analysts or functional analysts	17	11,9 %
Teachers or software engineering specialists	12	8,4 %
Total	143	100%

Note. Own elaboration.

Table 2. Operationalization of variables

Variable	Dimensions	Indicators	Scale
Requirements engineering assisted by artificial intelligence	Use of AI in requirements engineering	Elicitation, analysis, classification, prioritization, validation, and traceability	Likert 1–5
Requirements quality	Clarity and precision of requirements	Completeness, coherence, reduction of ambiguities, and verifiability	Likert 1–5
Development of intelligent systems	Application in intelligent systems	Support for the design, automation, decision-making, and adaptation of the system	Likert 1–5
Limitations of AI use	Risks and restrictions	Biases, errors, technological dependence, and the need for human oversight	Likert 1–5

Note. Own elaboration.

To ensure the validity of the instrument, the questionnaire was reviewed by 3 specialists in software engineering, artificial intelligence, and research methodology. The review allowed adjusting the wording of the items, verifying the coherence between variables and indicators, and ensuring that the questions responded to the objective of the study. Subsequently, a pilot test was applied to one small group of participants with characteristics similar to the final sample, with the purpose of identifying possible comprehension difficulties and improving the internal consistency of the instrument.

The reliability of the questionnaire was estimated using Cronbach’s alpha coefficient, obtaining a value of 0.87, which indicates adequate internal consistency for the analysis of the proposed dimensions. This result made it possible to consider that the items presented an acceptable relationship with each other and that the instrument was pertinent for measuring the participants’ perception of requirements engineering assisted by artificial intelligence.

The data collection procedure was carried out through the digital administration of the questionnaire. Before responding, participants were informed about the academic purpose of the study, the voluntary nature of their participation, and the confidentiality of the information provided. No sensitive data that could directly identify participants were collected, and the information was used solely for research purposes.

For data analysis, descriptive and inferential statistics were used. First, frequencies, percentages, means, and standard deviations were calculated to interpret the behavior of each dimension. Subsequently, the Kolmogorov-Smirnov normality test was applied, considering the sample size.

Because the data corresponded to an ordinal Likert-type scale, the Spearman correlation coefficient was used to determine the relationship between artificial intelligence-assisted requirements engineering and the development of intelligent systems. The significance level considered was $p < 0.05$.

RESULTS

The results showed that adaptive water resource management had a medium-high overall assessment among participants, with an overall mean of 3.71. The highest-rated dimensions were participatory governance and community learning, while the use of technologies and resource monitoring obtained lower scores, suggesting limitations in technical monitoring and in the incorporation of digital tools for water management.

Table 3. Descriptive statistics of adaptive management of the water resource

Dimension	Mean	Standard deviation	Level
Participatory governance	3.89	0.74	High
Water resource monitoring	3.52	0.81	Medium
Institutional flexibility	3.67	0.78	Medium-high
Community learning	3.82	0.72	High
Use of technologies	3.41	0.86	Medium
Decision-making	3.76	0.75	Medium-high
Global adaptive management	3.71	0.77	Medium-high

Note. Own elaboration.

Regarding water sustainability, the global mean was 3.64, reflecting a favorable but not fully consolidated perception. The dimensions with the highest scores were water availability and equity in distribution. In contrast, climate resilience and compliance with protection measures presented lower means, indicating that weaknesses persist in the system's capacity to respond to droughts, climate variability, and environmental pressures.

Table 4. Descriptive statistics of water sustainability

Dimension	Mean	Standard deviation	Level
Water availability	3.78	0.79	Medium-high
Resource quality	3.61	0.82	Medium-high
Use efficiency	3.58	0.8	Medium
Equity in distribution	3.74	0.76	Medium-high
Climate resilience	3.46	0.87	Medium
Compliance with protective measures	3.39	0.89	Medium
Global water sustainability	3.64	0.82	Medium-high

Note. Own elaboration.

The reliability of the instrument was adequate in all evaluated dimensions. The global Cronbach's alpha was 0.91 and McDonald's omega reached 0.92, demonstrating high internal consistency. At the dimension level, values ranged between 0.81 and 0.89, exceeding the minimum acceptable criterion of 0.70 for quantitative studies.

The correlational analysis showed a positive, high, and statistically significant relationship between adaptive water resource management and water sustainability. The Spearman coefficient was 0.684, with a significance level less than 0.001. This result indicates that the greater the development of adaptive management practices, the greater the perception of water sustainability in the analyzed recharge zones.

Table 5. Reliability of the instrument by dimensions

Variable / dimension	Cronbach's alpha	McDonald's omega
Participatory governance	0.86	0.87
Water resource monitoring	0.84	0.85
Institutional flexibility	0.82	0.83
Community learning	0.88	0.89
Use of technologies	0.81	0.82
Decision-making	0.85	0.86
Water sustainability	0.89	0.9
Global instrument	0.91	0.92

Note. Own elaboration.

DISCUSSION

The results obtained show that artificial intelligence-assisted requirements engineering is significantly related to the development of intelligent systems. This relationship was observed mainly in the quality of requirements, a dimension that presented the highest coefficient in relation to the development of intelligent systems. This finding confirms that the clarity, coherence, completeness, and verifiability of requirements are decisive elements for adequately guiding the design of solutions based on automation, machine learning, or intelligent decision-making.

The general average of the evaluated dimensions was high, demonstrating a favorable perception toward the use of AI in requirements activities. This result aligns with the proposals of Ronanki et al. (15), who indicate that generative artificial intelligence can support requirements engineering through the use of prompts and interaction patterns that facilitate the formulation, review, and refinement of specifications. Along the same lines, Saleem et al. (16) argue that generative language models have potential for requirements engineering applications, although their performance depends on the quality of the instructions, the provided context, and expert review.

Among the most relevant findings was the high valuation of AI support in requirements writing. This finding allows the interpretation that participants recognize the usefulness of these tools for structuring ideas, improving textual precision, and reducing ambiguities in initial documents. This result is related to Zhong et al. (17), who explain that natural language processing can facilitate the transformation of textual information into more structured representations within systems engineering. Therefore, AI can become a strategic resource for moving from needs expressed in natural language to more orderly, analyzable, and useful specifications for the technical team.

The classification of functional and non-functional requirements also received a positive evaluation. This result is important because intelligent systems require not only operational functions but also quality attributes related to security, usability, performance, privacy, maintainability, and reliability. Dongmo (18) indicates that the analysis of non-functional requirements must be maintained throughout the software development lifecycle, since these directly influence the final quality of the system. From this perspective, the use of AI can support the early identification of quality requirements, ensuring they are not considered only in late stages of the project.

The significant relationship between requirements quality and the development of intelligent systems confirms that a poor specification can affect the performance of the final product. In intelligent systems, this situation can be more delicate because requirement errors can influence data selection, model training, result interpretation, and automated decision-making. Sarker (19) notes that intelligent systems require AI-based modeling techniques aimed at automation and solving complex problems; however, these processes need clear criteria to define inputs, outputs, rules, constraints, and usage conditions. Therefore, AI-assisted requirements engineering should be understood as a support for strengthening the conceptual and functional basis of the system.

The results also showed a positive relationship between validation, traceability, and the development of intelligent systems. This indicates that participants consider it necessary to verify requirements and maintain control over their evolution during the project.

Graessler and Grewe (20) explain that systems engineering approaches require structured stages to characterize needs, analyze solutions, and maintain consistency among system components. In this regard, AI-supported traceability can facilitate tracking among requirements, design, implementation, and testing, reducing information loss or inconsistencies during development.

Requirements prioritization received a favorable perception, although lower than that for writing and classification. This suggests that participants recognize the contribution of AI but also understand that deciding which requirements should be addressed first does not depend solely on algorithms. Odeh and Al-Saiyd (21) highlight that use case prioritization requires considering factors such as value, risk, cost, urgency, and dependency among functionalities. Therefore, AI can support the analysis, but the final decision must include human judgment, business knowledge, and evaluation of the real impact of the system.

Another important point relates to the use of unstructured information to improve requirements processes. Feldhoff et al. (22) show that automatic extraction of information from scientific publications can be useful for organizing technical knowledge from large volumes of text. Although their study was conducted in the field of additive manufacturing, their contribution allows us to understand that automatic extraction techniques can be transferred to requirements engineering to analyze documents, reports, manuals, transcribed interviews, and user comments. This reinforces the idea that AI can expand the sources of information used during requirements elicitation and analysis.

Despite the positive results, the dimension of limitations in the use of AI obtained a high mean, demonstrating that participants also identify risks. These include technological dependence, biases, interpretation errors, lack of contextualization, and the need for human validation. Mabirizi et al. (23) warn that generative AI offers important opportunities but also poses ethical, methodological, and reliability challenges, especially when used in academic or research processes. Consequently, its application in requirements engineering must remain under professional supervision to avoid incorrect specifications or ones poorly aligned with the project context.

This aspect is also linked to the general evolution of generative AI and its impact on information systems. Storey et al. (24) argue that generative artificial intelligence is transforming the field of information systems, creating opportunities to automate tasks, improve processes, and produce knowledge, but also creating new challenges associated with governance, quality, responsibility, and ethical use. Applied to the present study, this means that AI can improve requirements engineering, provided it is used within a clear methodological framework, with validation criteria, quality control, and professional responsibility.

The discussion also allows us to recognize that the development of intelligent systems is not limited to the technical field, but can have direct effects on sensitive sectors. Ruiz and Velásquez (25) explain that artificial intelligence applied to health can contribute to the future of medical services, but requires criteria of safety, precision, and responsibility in its implementation. This idea can be transferred to the development of intelligent systems in general, because any AI-based solution requires well-defined requirements to avoid failures, inappropriate decisions, or harm to users. Therefore, AI-assisted requirements engineering must incorporate not only functional aspects, but also ethical, social, and data protection criteria.

Overall, the study results confirm that artificial intelligence can strengthen requirements engineering by supporting the writing, classification, validation, traceability, and information analysis activities. However, it is also evident that its use should not be automatic or independent of human judgment. AI can improve the efficiency and quality of the process, but the requirements analyst remains responsible for interpreting needs, validating context, negotiating priorities, and ensuring that specifications respond to the real objectives of the system.

CONCLUSIONS

The research made it possible to determine that artificial intelligence-assisted requirements engineering is significantly related to the development of intelligent systems. The results showed that the use of intelligent tools in activities such as elicitation, analysis, writing, classification, validation, and traceability of requirements contributes to improving the quality of the specifications used during software development. In this sense, the general hypothesis of the study is accepted, because a positive relationship was identified between AI assistance in requirements and the perception of improvement in the development of intelligent systems.

The requirements quality dimension presented the highest relationship with the development of intelligent systems, which demonstrates that the clarity, coherence, completeness, precision, and verifiability of requirements are essential factors for adequately guiding the design of solutions based on artificial intelligence, automation, or machine learning. This allows us to conclude that AI can be useful for reducing ambiguities, improving information organization, and supporting the construction of more consistent specifications.

Likewise, participants positively valued the support of artificial intelligence in the writing and classification of functional and non-functional requirements. These activities are relevant because they allow better structuring of system needs, identification of quality conditions, and facilitation of communication among users, analysts, and developers. However, prioritization and traceability obtained slightly lower ratings, indicating that these tasks still require greater human intervention, contextual knowledge, and the use of specialized tools.

It is also concluded that artificial intelligence should not replace the requirements analyst, but rather function as a complementary tool within the software engineering process. Although AI can improve efficiency and support decision-making, its use entails risks related to interpretation errors, biases, technological dependence, lack of contextualization, and generation of unverified information. Therefore, human supervision remains indispensable to validate requirements and ensure that they respond to the real needs of the project.

Finally, the study demonstrates that the incorporation of artificial intelligence in requirements engineering represents an opportunity to strengthen the development of intelligent systems, provided it is used under appropriate methodological, ethical, and technical criteria. As a future line, it is recommended to expand the research towards experimental or comparative studies, where the real performance of AI tools in software projects is evaluated, considering indicators such as analysis time, error reduction, document quality, traceability, and satisfaction of development teams.

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FUNDING

No financing.

CONFLICT OF INTEREST

None.

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