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ORIGINAL

Application of artificial intelligence in the optimization of software engineering processes

Aplicación de inteligencia artificial en la optimización de procesos de ingeniería de software

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ABSTRACT

The main purpose of this research was to carry out an analysis of the use of artificial intelligence in the optimization of software engineering processes of professionals from companies in Chile, Ecuador and México, through a study that was structured with a quantitative, non-experimental approach and with a descriptive-correlational scope of a cross-sectional type. The research sample was made up of 210 professionals from the three countries. A survey was used for data collection using the five-level Likert scale, which included dimensions related to task automation, software quality, defect prediction, decision-making, productivity, and efficiency of the development process; Cronbach's alpha to determine the reliability of the instrument was 0.89. The results showed that the degree of use of artificial intelligence and the degree of process optimization obtained high values (general mean of 4.08 and 4.12 respectively). A moderate-high positive correlation was also found between both variables using Spearman's Rho of 0.682. It concludes that artificial intelligence contributes to improving the level of productivity, quality and efficiency around the software engineering process in the context of Latin American companies.

Keywords: artificial intelligence; software engineering; process optimization; automation; software quality.

RESUMEN

El propósito fundamental de la presente investigación fue realizar un análisis de la utilización de la inteligencia artificial en la optimización de procesos de la ingeniería del software de los profesionales de las empresas de Chile, Ecuador y México, a través de un estudio que se estructuró con un enfoque cuantitativo, no experimental y con un alcance descriptivo-correlacional de tipo transversal. La muestra de la investigación estuvo conformada por 210 profesionales de los tres países. Se usó una encuesta para la recolección de datos mediante la escala de Likert a cinco niveles en la que se incluyeron dimensiones relacionadas a la automatización de tareas, calidad del software, predicción de defectos, toma de decisiones, productividad y eficiencia del proceso de desarrollo; el alfa de Cronbach para determinar la confiabilidad del instrumento fue de 0,89. Los resultados mostraron que el grado de utilización de la inteligencia artificial y el de optimización de procesos obtuvieron valores altos (media general de 4,08 y 4,12 respectivamente). También se encontró una correlación positiva moderada-alta entre ambas variables mediante Rho de Spearman de 0,682. Concluye que la inteligencia artificial contribuye a mejorar el nivel de productividad, calidad y eficiencia en torno al proceso de la ingeniería del software en el contexto de las empresas latinoamericanas.

Palabras clave: inteligencia artificial; ingeniería de software; optimización de procesos; automatización; calidad del software.

INTRODUCTION

AI has become the fundamental technology to revolutionize the tasks of software engineering processes, such as project management; the preparation of requirements; programming; testing, maintenance; code audits, defect prediction or quality management. In the business world, the development of new computer systems is carried out under increasingly tight time cycles and there is also a greater demand for efficiency and the obligation to build quality software. Intelligent models make it possible to carry out routine tasks, anticipate errors, as well as even make explicit technical decisions within the software lifecycle. This fact not only affects the way technological solutions or digital goods are designed, but also the way in which work groups reorganize their internal work in the organization.

Contemporary software engineering faces challenges related to the complexity of systems, the variability of requirements, the reduction of delivery times and the need to ensure quality standards in highly competitive environments.Ahmad et al. (2023)point out that the integration of artificial intelligence in requirements engineering makes it possible to orient development towards systems more focused on human needs. In a complementary way, AI applied to software development favors automation, error reduction, and the improvement of technical processes when it is integrated in a planned way into the activities of the software life cycle(Almeida et al., 2024).

One of the fields where artificial intelligence has shown greater applicability is the prediction and detection of defects.Al-Smadi et al. (2023)argue that interpretable machine learning models strengthen the reliable prediction of software defects, which is relevant for improving traceability and technical decision-making. This predictive capability allows teams to prioritize remediation activities, identify critical modules, and reduce risks before errors impact the quality of the final product. In this sense, early defect prediction is an important resource for optimizing quality management in software development(Falessi et al., 2023).

Intelligent automation has also gained importance in software testing and defect management.García et al. (2026)explain that test automation with tools such as Selenium represents a widespread practice to improve the efficiency of quality assurance. These tools reduce manual intervention, increase assessment coverage, and accelerate the identification of functional inconsistencies. In turn, automatic defect analysis using artificial intelligence can improve reporting, order incidents, and support corrective decisions within development teams(Esposito et al., 2024).

Another relevant axis is the influence of generative artificial intelligence on the performance of software development.Chang and Huang (2026)analyze the impact of generative AI on development productivity and warn that its incorporation can modify the relationship between technical capacity, performance, and technological dependence. Generative tools have begun to be used to assist in writing code, documenting functionalities, generating tests, explaining complex snippets, and supporting technical problem solving. This process shows that AI not only acts as a supporting technology, but as a component that redefines professional practices in software engineering.

Process optimization is not limited to code development, but also encompasses workflow automation, operations management, and continuous improvement.Filgueiras et al. (2022)show that robotic process automation can transform the user experience after its organizational adoption. Along the same lines, intelligent automation can improve operational efficiency when implemented in structured processes and with clear control, monitoring, and evaluation criteria(Lievanó-Martínez et al., 2022). Therefore, its application in software engineering must be analyzed from a technical and organizational perspective.

Incorporating artificial intelligence into business processes also poses administrative, social, and innovative challenges.HuacasiAñamuroet al. (2025)point out that automation and robotics generate challenges related to organizational adaptation, change management, and entrepreneurial innovation. These factors are relevant for software development companies, where AI adoption depends not only on technological availability, but also on professional training, organizational culture, and the digital maturity of the teams. Therefore, the optimization of processes through AI requires institutional conditions that allow its responsible implementation.

From a broader perspective, artificial intelligence applied to optimization requires considering technical benefits along with criteria of security, sustainability, interpretability and trust.Aslam et al. (2025)warn that AI-based systems must respond to safety and sustainability challenges, especially when applied in industrial and control processes. In software engineering, this condition is critical, because automated recommendations can influence decisions about architecture, testing, maintenance, and product quality. Confidence in algorithmic results depends, to a large extent, on the transparency and explanatory capacity of the models used.

The explainability of artificial intelligence has become a key criterion for its application in professional contexts.Saranya and Subhashini (2023)highlight that explainable models allow for a better understanding of the results produced by algorithms and facilitate their acceptance by users. This feature is important in software engineering, because professionals need to justify technical decisions, validate predictions, and understand the causes of detected defects. AI-based optimization must therefore be oriented not only to efficiency, but also to the responsible interpretation of the results obtained.

Recent literature also shows that artificial intelligence can increase research and production efficiency in engineering areas.MadanchianandTaherdoost[2025]argue that AI contributes to improving the efficiency of processes associated with research, analysis, and knowledge production. Although this contribution comes from a broad field, it allows us to understand that AI optimization is linked to the reduction of times, improvement of accuracy, automation of tasks and strengthening of decisions based on data. Similarly, AI-based technical optimization has shown potential to improve the performance of specialized engineering processes(Ullrich et al, 2024).

The evolution of artificial intelligence has expanded its practical applications in various professional sectors, which reinforces its transversal nature.Basáezand Mora (2022)argue that AI has evolved towards increasingly specific applications, aimed at solving specific problems through automated analysis and data learning. This condition allows its contributions to be transferred to the field of software engineering, where processes require precision, efficiency and adaptability. Consequently, its application must be studied considering both its technical benefits and the real conditions of use in Latin American companies.

Despite these advances, there is still a need to empirically study how software engineering professionals perceive and use artificial intelligence to optimize their work processes in Latin American business contexts. Many studies have focused on specific tools, technical models or isolated applications, but more quantitative evidence is required on the relationship between the use of AI, process automation, software quality, productivity and decision-making in companies in different countries. This gap is relevant because Chile, Ecuador and Mexico present different dynamics of digital transformation, technological adoption and organizational maturity.

In this sense, the objective of this study is to analyze the application of artificial intelligence in the optimization of software engineering processes in professionals from companies in Chile, Ecuador and Mexico. The research adopts a quantitative approach, with a descriptive-correlational scope and a non-experimental design, with a sample of 210 participants distributed among the three countries. The study considers dimensions associated with task automation, software quality improvement, defect prediction, decision support, team productivity, and perception of efficiency in development processes. With this, it seeks to provide empirical evidence on the role of artificial intelligence in the improvement of software engineering processes within Latin American organizations.

METHODS

The research was developed under a quantitative approach, because it allowed to objectively measure the application of artificial intelligence in the optimization of software engineering processes. This approach was pertinent because the study was oriented to the analysis of numerical data obtained through a structured instrument, which facilitated the identification of trends, levels of perception and relationships between the dimensions evaluated. The design was non-experimental, since variables were not manipulated, but the perceptions of the participants in their real work context were observed. In addition, the study had a descriptive-correlational scope, because it first characterized the use of artificial intelligence in software engineering processes and then examined the relationship between its main dimensions.

The population was made up of professionals linked to software development, technology, computer consulting and digital transformation companies from Chile, Ecuador and Mexico. The participants corresponded to profiles related to systems analysis, software development, quality assurance, technology project management, DevOps, software architecture and specialized technical support. The sample was made up of 210 professionals, selected through non-probabilistic sampling for convenience, considering as the main criterion direct or indirect experience in software engineering processes and the use or knowledge of tools based on artificial intelligence.

The distribution of the sample was balanced among the three participating countries. In Chile, 70 professionals were considered, in Ecuador 70 professionals and in Mexico 70 professionals. This distribution made it possible to compare perceptions between Latin American business contexts and to obtain a regional vision on the incorporation of artificial intelligence in software engineering processes. As inclusion criteria, it was established that the participants were of legal age, worked or had worked in companies related to the development of software or technological services, and agreed to participate voluntarily in the study. Incomplete, duplicate or issued responses by people with no professional relationship with the study area were excluded.

The technique used for data collection was the survey, applied through a questionnaire structured on a five-level Likert scale, where 1 represented "strongly disagree" and 5 "strongly agree". The instrument was designed to measure the perception of professionals about the application of artificial intelligence in the optimization of software engineering processes. The questionnaire consisted of 24 items, distributed in six dimensions: task automation, improvement of software quality, prediction and detection of defects, decision support, team productivity and efficiency of the development process.

The operationalization of the variables allowed the dimensions, indicators, and measurement scale of the study to be organized in a coherent manner. The independent variable was the application of artificial intelligence, understood as the use of tools, models and intelligent systems to support software engineering activities. The dependent variable was the optimization of software engineering processes, understood as the improvement in efficiency, quality, productivity, decision-making and reduction of errors within the development life cycle.

Table 1. Operationalization of the study variables

Variable	Dimensions	Indicators	Items	Scale
Application of artificial intelligence	Task automation	Reduction of repetitive activities, acceleration of workflows, support in technical tasks	1–4	Likert 1–5
Application of artificial intelligence	Improved software quality	Code review, functional validation, error abatement, quality control	5–8	Likert 1–5
Application of artificial intelligence	Defect Prediction and Detection	Early identification of faults, prioritization of fixes, technical risk analysis	9–12	Likert 1–5
Application of artificial intelligence	Decision support	Automated recommendations, data analysis, support for technical and managerial decisions	13–16	Likert 1–5
Software Engineering Process Optimization	Team Productivity	Reduction of times, improvement of professional performance, coordination of tasks, fulfillment of deliveries	17–20	Likert 1–5
Software Engineering Process Optimization	Development Process Efficiency	Resource optimization, lifecycle improvement, process integration, operational efficiency	21–24	Likert 1–5

Note. The table presents the relationship between the variables, dimensions and indicators used to measure the application of artificial intelligence in the optimization of software engineering processes. Own elaboration.

To ensure the validity of the instrument, an expert review process was applied. Three specialists with experience in software engineering, artificial intelligence and quantitative research methodology participated. The experts reviewed the clarity, relevance and coherence of the items with the proposed dimensions. Based on their observations, wording adjustments were made to avoid ambiguities and improve the technical accuracy of the questions. Subsequently, a pilot test was carried out with 20 professionals who were not part of the final sample, in order to verify the understanding of the questionnaire and estimate its initial reliability.

The reliability of the instrument was determined by Cronbach's alpha coefficient. The overall result reached a value of 0.89, which evidenced an adequate internal consistency for the development of the study.

This value allowed us to consider that the questionnaire items were coherent with each other and stably measured the dimensions associated with the application of artificial intelligence in the optimization of software engineering processes. Consistency by dimensions was also reviewed, obtaining acceptable values in task automation, software quality, defect prediction, decision-making, productivity and process efficiency.

The data collection procedure was developed in three phases. In the first phase, companies and professionals related to software engineering were identified in Chile, Ecuador and Mexico. In the second phase, the purpose of the research was socialized, informed consent was requested, and the questionnaire was applied in digital format. In the third phase, the database was cleansed, eliminating incomplete or inconsistent responses. The implementation of the instrument was carried out over a period of four weeks, ensuring that participants responded voluntarily, anonymously and without institutional pressure.

The data were analyzed through descriptive and inferential statistics. In the descriptive analysis phase, frequencies, percentages, means and standard deviations were calculated up to the range evaluated in each dimension of artificial intelligence. In the inferential phase, the Kolmogorov-Smirnov test was applied to determine normality as a function of sample size. Based on the shape of the data, Spearman's correlation coefficient was used to explore the relationship between artificial intelligence and software engineering process optimization. Country comparisons were also made to see if there were differences between the groups in Chile, Ecuador and Mexico.

In reference to ethical considerations, the results were assured in their confidentiality, not requesting sensitive personal data or those that would allow the direct identification of the participating professionals or companies. Participation was voluntary and the study aims were previously informed, the academic use of the information and the possibility of being able to withdraw during the course of the study. Finally, the results were worked on in an aggregate manner and complying with the principles of anonymity, informed consent and research responsibility.

RESULTS

The results were organized according to the objective of the study, aimed at analyzing the application of artificial intelligence in the optimization of software engineering processes in professionals from companies in Chile, Ecuador and Mexico. To this end, the general characteristics of the sample, the levels obtained by dimension, the comparison between countries and the correlational analysis between the main variables are presented.

Table 2. Characterization of the participants

Feature	Category	Frequency	Percentage
Country	Chile	70	33,3%
Country	Ecuador	70	33,3%
Country	Mexico	70	33,3%
Professional profile	Software Developers	62	29,5%
Professional profile	Systems Analysts	38	18,1%
Professional profile	Quality Assurance	34	16,2%
Professional profile	Technology project managers	31	14,8%
Professional profile	DevOps Specialists	25	11,9%
Professional profile	Software Architects	20	9,5%

Note. The sample was made up of 210 professionals distributed in a balanced manner between Chile, Ecuador and Mexico. Own elaboration.

Table 2 shows a balanced distribution by country, with 70 professionals in Chile, 70 in Ecuador and 70 in Mexico. This organization allowed for proportional representation of the three Latin American business contexts analyzed. In terms of professional profile, the group with the highest presence was software developers, with 29.5%, followed by systems analysts, with 18.1%, and quality assurance professionals, with 16.2%. This composition was pertinent to the study, because the participants work in areas directly related to the software life cycle, such as analysis, coding, testing, integration, quality control and management of technological projects.

Table 3. Application level of artificial intelligence and process optimization

Variable/Dimension	Media	Standard deviation	Level
Task automation	4,18	0,61	High
Improved software quality	4,11	0,64	High
Defect Prediction and Detection	3,96	0,68	High
Decision support	4,05	0,66	High
Application of artificial intelligence	4,08	0,65	High
Team Productivity	4,14	0,63	High
Development Process Efficiency	4,09	0,67	High
Software Engineering Process Optimization	4,12	0,65	High

Note. The scale used was from 1 to 5, where values greater than 3.67 indicate a high level. Own elaboration.

The results in Table 3 show that the application of artificial intelligence presented a high level, with a general average of 4.08. The best-rated dimension was task automation, with an average of 4.18, indicating that professionals perceive AI as a useful resource to reduce repetitive activities, speed up workflows, and support technical tasks. The improvement in software quality obtained an average of 4.11, reflecting a favorable perception of the use of AI in code review, functional validation and error reduction.

The prediction and detection of defects reached an average of 3.96. Although it was also at a high level, it was the dimension with the lowest score within the variable application of artificial intelligence. This result suggests that its implementation may depend on the availability of historical data, specialized tools, and technical training of the teams. On the other hand, decision support registered an average of 4.05, which shows that participants recognize the value of automated analyses and data-driven recommendations to guide technical decisions.

Regarding the optimization of software engineering processes, the general average was 4.12, also located at a high level. The team's productivity reached an average of 4.14, which indicates that professionals consider AI to contribute to improving performance, reducing times and facilitating task coordination. The efficiency of the development process obtained an average of 4.09, evidencing that AI is perceived as a support to optimize resources, improve the software life cycle and reduce manual activities.

Table 4. Comparison of results by country

Country	Application of AI	Process optimization	General level
Chile	4,15	4,18	High
Ecuador	4,01	4,05	High
Mexico	4,08	4,12	High
Overall average	4,08	4,12	High

Note. The averages correspond to the average rating obtained by country. Own elaboration.

Table 4 shows that the three countries presented high levels both in the application of artificial intelligence and in the optimization of processes. Chile recorded the highest averages, with 4.15 in AI application and 4.18 in process optimization. Mexico presented intermediate values, with 4.08 and 4.12, while Ecuador obtained averages of 4.01 and 4.05. While the differences are not wide, the results suggest that the perception of AI adoption and leverage may vary depending on digital maturity, business practices, and the previous experience of technology teams.

These findings show a favorable regional trend towards the incorporation of artificial intelligence in software engineering. The difference between countries does not change the overall pattern of the study, as a positive assessment of AI use was identified in all three contexts. However, the variations observed may be useful to guide future comparative research or specific studies on implementation barriers, professional training, and availability of smart tools in Latin American companies.

Table 5 presents the analysis of normality and correlation. In the Kolmogorov-Smirnov test, the application of artificial intelligence obtained a significance of 0.001 and the optimization of software engineering processes a significance of 0.002. As these values were less than 0.05, it was determined that the data did not follow a normal distribution. For this reason, Spearman's Rho coefficient was used to analyze the relationship between the variables.

The correlational analysis showed a moderate-high positive relationship between the application of artificial intelligence and the optimization of software engineering processes, with a Rho of 0.682 and a significance of 0.000. This result indicates that, the greater the application of AI in activities such as automation, quality improvement, defect prediction and decision-making, the greater the perception of optimization in software development processes. Although the non-experimental design does not allow causality to be established, the association found confirms that both variables are significantly related.

Table 5. Analysis of normality and correlation between variables

Analysis	Variable/Ratio	Statistician	Sig.	Interpretation
Kolmogorov-Smirnov	Application of artificial intelligence	0,126	0,001	Non-normal distribution
Kolmogorov-Smirnov	Software Engineering Process Optimization	0,119	0,002	Non-normal distribution
Spearman's Rho	Application of AI / Process Optimization	0,682	0,000	Moderate-high positive correlation
Spearman's Rho	Task Automation / Process Optimization	0,641	0,000	Moderate-high positive correlation
Spearman's Rho	Software Quality / Process Optimization	0,618	0,000	Moderate-high positive correlation
Spearman's Rho	Defect Prediction / Process Optimization	0,574	0,000	Moderate positive correlation
Spearman's Rho	Decision Making / Process Optimization	0,603	0,000	Moderate-high positive correlation

Note. Correlations were significant at the bilateral level of 0.01. Own elaboration.

When reviewing the dimensions, task automation showed the highest correlation with process optimization, with a Rho of 0.641. This shows that reducing repetitive activities and speeding up workflows are associated with higher levels of efficiency. The improvement of the quality of the software also showed an important relationship, with a Rho of 0.618, which shows that the use of AI for review, validation and error control contributes to improving the perception of the technical process. Decision support reached a Rho of 0.603, while prediction and defect detection obtained a Rho of 0.574, remaining a positive and significant relationship.

In summary, the results show that professionals in Chile, Ecuador and Mexico perceive a high application of artificial intelligence in software engineering processes. The dimensions with the highest valuation were the automation of tasks and team productivity, which shows that AI is recognized mainly for its contribution to the reduction of times and improvement of work performance. In addition, the positive correlation found confirms that the application of AI is significantly associated with process optimization, especially in activities related to automation, quality, decision-making, and operational efficiency.

DISCUSSION

The results of the study showed that the application of artificial intelligence in software engineering processes was perceived at a high level by professionals in Chile, Ecuador and Mexico. This finding confirms that AI has ceased to be a complementary tool and has become a strategic resource within technical processes, especially in activities related to automation, quality control, error prediction and decision-making. The overall average obtained in the application of AI reflects a positive assessment of the participants, which suggests that professionals recognize its usefulness in optimizing tasks, reducing times and improving the performance of development teams.

These results coincide withAracena et al. (2022), who point out that machine learning makes it possible to automate complex analyses and strengthen response capacity in contexts where there is a high volume of data. Although his study is located in the field of health, his contributions allow us to understand that AI has a transversal logic applicable to different sectors, including software engineering. In this study, this transversality is observed in the positive assessment of task automation, a dimension that obtained the highest average. This indicates that professionals perceive AI as a direct support to reduce repetitive processes and improve operational efficiency.

Task automation was the most highly valued dimension within the application of artificial intelligence. This result shows that professionals identify greater benefits when AI is used to accelerate workflows, support technical activities and reduce manual burdens. In relation to this,Ávila-Tomás et al. (2021)argue that the practical applications of artificial intelligence are aimed at improving processes through automated analysis and support for specialized decisions. In the context of software engineering, this input is reflected in activities such as assisted code generation, test automation, technical documentation, bug review, and incident management.

Software quality improvement was also high, demonstrating that participants recognize AI's contribution to code review, functional validation, and error reduction. This result is related to what was proposed byBarea Mendoza et al. (2025), who highlight that the use of artificial intelligence can contribute to strengthening the safety and quality of processes when applied with appropriate technical criteria. Although its analysis corresponds to the field of the critical patient, the idea of safety, control and precision can be transferred to software development, where the quality of the product depends on the ability to detect faults, validate functionalities and prevent risks before final delivery.

Another relevant result was the high valuation of AI as a support for decision-making. Participating professionals felt that automated recommendations and data-driven analysis can guide technical and managerial decisions within development teams. This finding agrees withDorado-Díaz et al. (2019), who explain that artificial intelligence makes it possible to analyze large volumes of information and support specialized decisions in scenarios where accuracy is essential. In software engineering, this ability is expressed in the prioritization of defects, allocation of resources, estimation of efforts, selection of tools and evaluation of the progress of projects.

The dimension of prediction and detection of defects obtained a high level, although with a lower average compared to the other dimensions of the AI application. This result can be explained by the fact that defect prediction requires historical databases, trained models, integration with code repositories, and teams with specific analytical competencies.Gimeno-Ballester and Trigo-Vicente (2024)warn that the use of artificial intelligence in professional processes must be accompanied by criteria of integrity, human review, and responsibility in the interpretation of results. In this sense, the lower relative valuation of this dimension does not imply rejection of AI, but a possible caution against processes that require greater technological maturity.

The moderate-high positive correlation between the application of artificial intelligence and the optimization of software engineering processes confirms that both variables are significantly related. This result shows that professionals who perceive a greater use of AI also report better levels of productivity and efficiency in development processes.Avello-Sáez et al. (2024)point out that the incorporation of AI in academic and professional contexts requires a clear statement of use, integrity criteria, and understanding of its scope. In the present study, this perspective is useful to interpret that optimization does not depend only on adopting intelligent tools, but also on using them under technical, ethical and organizational criteria.

The comparison by country showed high levels in Chile, Ecuador and Mexico, although Chile registered the highest averages. This difference can be related to different levels of digital maturity, technological investment, professional training and business adoption of intelligent tools. However, the general trend was favorable in the three countries, which shows that AI is being progressively incorporated into software engineering processes in the region. This result coincides with Díaz-Guio et al. (2026), who identify that knowledge, practices, and perceptions about AI can vary according to the institutional and professional context, especially in Latin America.

The results also allow us to affirm that artificial intelligence positively influences team productivity. Participants perceived that AI contributes to reducing times, improving performance and facilitating task coordination. This perception is related toMartínez-Comesañaet al. (2023), who argue that AI can transform evaluation and monitoring processes by incorporating automated mechanisms to analyze information and generate more efficient responses. In software engineering, this logic is expressed in the ability to monitor progress, detect inconsistencies, generate reports, and support activities that previously required greater manual intervention.

The efficiency of the development process has also reached a high level, which shows that professionals believe that AI can optimize resources and improve the software life cycle. ReyesGrangelet al. (2026)explain that artificial intelligence must be understood from its general concepts, scope, and real possibilities of application, avoiding reductionist interpretations or excessive expectations. From this perspective, the results of this study show a positive assessment, but they also invite us to understand that efficiency depends on the proper integration of AI with development methodologies, professional competencies and defined organizational processes.

The findings also relate to user experience and quality of technological service.Rubio et al. (2025)suggest that artificial intelligence can improve the user experience when used to personalize processes, anticipate needs, and strengthen care. In software engineering, this idea can be transferred to the development of digital products that are more reliable, adaptable, and aligned with the needs of end users. Therefore, process optimization should not only be understood as a reduction in time, but also as an improvement in the quality, traceability, responsiveness and satisfaction of those who use the solutions developed.

Overall, the results confirm that artificial intelligence is significantly related to the optimization of software engineering processes in companies in Chile, Ecuador and Mexico. Task automation, software quality improvement, and decision support were the most relevant aspects to explain this relationship.

CONCLUSIONS

It was verified that the integration of artificial intelligence in engineering processes reached a high perception according to the set of professionals working in companies in Chile, Ecuador and Mexico, so it may have reached a sphere where AI has gone from being considered a less relevant instrument to being recognized and seen as an important resource that serves to help those functional activities that can be used to be related to automation, code review, functional validation, and defect prediction in the software lifecycle.

The data reveal that automation was the dimension that had the highest rating, which led to the conclusion that professionals have an argument that is mainly based on seeing how artificial intelligence has advanced in the construction of dimensions such as automation to help reduce repetitive activities or the flourishing of work schemes. together with the contribution of operational performance; This expresses the fact that artificial intelligence helps to optimize times or complement technical processes that previously weighed more heavily on manual intervention.

The optimization of software engineering processes also showed a high level – especially in terms of team productivity and efficiency of the development process. In this way, it is possible to say that the use of artificial intelligence is associated with a better organization of tasks, a better use of resources, a lower number of errors and a reinforcement of the quality of the work carried out by technological teams.

The correlational analysis indicates that there is a moderately high positive relationship between the application of artificial intelligence and the optimization of software engineering processes. In this sense, it can be said that the greater the use of tools and systems supported by AI, the greater the perception of improvement in efficiency, productivity and quality of development processes. Despite the above, as it is a non-experimental design, the relationship should be considered from the assumption of a significant association and not as a causality.

The comparison between countries showed high levels in Chile, Ecuador and Mexico, with small variations in the averages obtained, which allows us to conclude that the application of artificial intelligence in software engineering presents a favourable regional trend, although its use may depend on contexts, such as digital maturity, professional training, technological availability (including the tools used) and organizational culture.

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Conceptualization: CBCT
Data Curation: TCCG
Formal analysis: TCCG
Research: CBT
Methodology: TCCG
Project Management: TCCG
Software: TCCG
Supervision: TCCG
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