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ORIGINAL

Optimization of software engineering processes through the application of artificial intelligence

Optimización de procesos de ingeniería de software mediante la aplicación de inteligencia artificial

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ABSTRACT

Artificial intelligence has become a strategic tool for improving processes related to software engineering, especially in activities associated with automation, data analysis, error detection, and the productivity of technological teams. This study aimed to analyze the relationship between the application of artificial intelligence, the optimization of software engineering processes, and software quality/productivity among workers from companies in Ecuador, Colombia, and Bolivia. The research was conducted under a quantitative approach, with a non-experimental design, descriptive-correlational scope, and cross-sectional nature. The sample consisted of 135 workers, proportionally distributed among the three countries. Data were collected through a structured survey using a five-point Likert scale, organized into three main variables. The results showed high mean scores for artificial intelligence application, process optimization, and software quality/productivity. In addition, positive and significant correlations were identified among the variables analyzed, with the strongest relationship found between process optimization and quality/productivity. It is concluded that artificial intelligence contributes to improving operational efficiency, reducing repetitive tasks, and strengthening software development quality, provided that its implementation is supported by training, human supervision, and appropriate technical criteria.

Keywords: artificial intelligence, software engineering, process optimization, productivity, software quality.

RESUMEN

La inteligencia artificial se ha convertido en una herramienta estratégica para mejorar los procesos asociados a la ingeniería de software, especialmente en actividades relacionadas con la automatización, el análisis de datos, la detección de errores y la productividad de los equipos tecnológicos. El presente estudio tuvo como objetivo analizar la relación entre la aplicación de inteligencia artificial, la optimización de procesos de ingeniería de software y la calidad/productividad del software en trabajadores de empresas de Ecuador, Colombia y Bolivia. La investigación se desarrolló bajo un enfoque cuantitativo, con diseño no experimental, alcance descriptivo-correlacional y corte transversal. La muestra estuvo conformada por 135 trabajadores, distribuidos proporcionalmente entre los tres países. Para la recolección de datos se aplicó una encuesta estructurada con escala Likert de cinco puntos, organizada en tres variables principales. Los resultados evidenciaron medias altas en aplicación de inteligencia artificial, optimización de procesos y calidad/productividad del software. Además, se identificaron correlaciones positivas y significativas entre las variables analizadas, destacando la relación entre optimización de procesos y calidad/productividad. Se concluye que la inteligencia artificial contribuye a mejorar la eficiencia operativa, reducir tareas repetitivas y fortalecer la calidad del desarrollo de software, siempre que su implementación se acompañe de capacitación, supervisión humana y criterios técnicos adecuados.

Palabras clave: inteligencia artificial, ingeniería de software, optimización de procesos, productividad, calidad del software.

INTRODUCTION

Software engineering currently faces the challenge of responding to increasingly dynamic business environments, where delivery speed, product quality, error reduction, and operational efficiency have become essential criteria for technological competitiveness. In this scenario, artificial intelligence has acquired a relevant role by being incorporated into different phases of the software life cycle, from planning and requirements analysis to assisted programming, automated testing, defect detection, and system maintenance. This evolution responds to the need to transform traditional processes into more agile and predictive models oriented toward data-driven decision-making (1,2).

The use of artificial intelligence in organizational contexts relates not only to task automation but also to improving productivity and company adaptability. Recent studies have shown that AI can positively influence business performance by optimizing resources, reducing operational times, and strengthening the analytical capacity of organizations (3,4). From this perspective, its application in software engineering represents an opportunity to improve processes that have historically depended on manual activities, subjective criteria, or reviews conducted after errors appear.

The integration of AI is also linked to organizational agility, as it enables a more flexible response to market changes, user needs, and the complexity of technological projects. Recent literature highlights that artificial intelligence can promote the strategic adaptation of organizations, especially when combined with agile management models, collaborative leadership, and innovation-oriented digital tools (5,6). In distributed or virtual development teams, these capabilities are particularly important, as they allow the coordination of tasks, the analysis of information, and the improvement of technical communication among project participants (7).

In the specific field of software engineering, generative artificial intelligence has driven new ways of working through coding assistants, documentation generation, error analysis, and support in technical decision-making. These tools do not replace the professional judgment of developers, but they can complement their activities by accelerating repetitive tasks, suggesting solutions, and reducing operational burdens during system development (8,9). Therefore, AI becomes a strategic resource to optimize internal processes, as long as its implementation is accompanied by ethical criteria, human validation, and quality control.

Likewise, technological project management has begun to incorporate artificial intelligence to improve planning, monitoring, and performance evaluation. In this regard, AI-based tools can support activity prioritization, risk analysis, resource estimation, and the identification of patterns that affect the achievement of objectives. Recent research on project management and open innovation shows that these technologies provide value when integrated in a structured manner into organizational processes, rather than as isolated solutions (10,11).

Another relevant aspect is the ability of artificial intelligence to strengthen decision-making in business environments. Through the processing of large volumes of information, intelligent systems can contribute to identifying trends, anticipating problems, and generating useful recommendations to improve operational efficiency. In this regard, recent bibliometric studies show sustained growth in academic interest in the relationship between AI, productivity, business management, and digital transformation (12,13). This trend confirms the need to study its impact in specific sectors, such as software development.

Process optimization through artificial intelligence is also related to the ability to formulate more efficient solutions to complex problems. From the perspective of computational optimization, AI can intervene in the generation of parameters, formulation of models, and selection of solution methods, which is useful for improving technical and operational decisions (14). Although these applications have been widely studied in various productive sectors, their application in software engineering requires further empirical analysis, especially in Latin American contexts, where technological adoption conditions may vary across companies and countries.

In addition, recent reviews in sectors such as construction and health show that AI and machine learning can be integrated into different stages of processes to improve planning, control, outcome prediction, and workflow efficiency (15,16). In education, their impact on assessment methods and web applications oriented to neuroscience teaching has been studied (17,18). In scientific publishing and care, their role as support for information processing and strengthening professional decisions has also been analyzed (19,20). Although these contributions come from different areas, they allow us to understand that AI-based optimization is not limited to a discipline but constitutes a cross-cutting trend in engineering processes. In the case of software, this trend manifests in test automation, programming assistance, predictive analytics, and continuous improvement of digital products.

Despite the advancement of these technologies, challenges still exist related to trust in AI-generated results, over-reliance on automated tools, staff training, and the need to evaluate their real impact on work processes. Therefore, it is necessary to analyze not only the availability of intelligent tools, but also workers' perception of their usefulness in optimizing activities, software quality, and team productivity. This perspective allows us to understand how AI is incorporated into professional practice and what effects are perceived in the performance of software engineering processes.

Based on the foregoing, this study aims to analyze the relationship between the application of artificial intelligence, the optimization of software engineering processes, and software quality/productivity in workers linked to technology companies in Latin America. Thus, it seeks to provide empirical evidence on the role of AI as a strategic resource to improve the development, control, and delivery of digital solutions in contemporary business environments.

METHODS

The study was developed under a quantitative approach, since numerical data were collected from the perceptions of workers involved in software engineering processes. The design was non-experimental, as the study variables were not manipulated, but rather analyzed as they presented themselves in the participants' work context. Likewise, it had a descriptive-correlational scope and a cross-sectional design, given that the information was collected at a single point in time with the purpose of identifying the behavior of the variables and the relationship between them.

The population consisted of workers from companies related to software development, technological services, IT consulting, and systems areas in organizations in Ecuador, Colombia, and Bolivia. For data collection, one sample of 135 workers was selected, distributed proportionally among the three countries considered in the study. Of this total, 45 participants corresponded to Ecuador, 45 to Colombia, and 45 to Bolivia. The selection was made using non-probabilistic convenience sampling, considering the availability of participants and their direct involvement in activities associated with the analysis, design, development, testing, maintenance, or management of software projects.

The variables analyzed were three: application of artificial intelligence, optimization of software engineering processes, and software quality/productivity. The first variable allowed identifying the level of use of AI tools in activities such as assisted programming, information analysis, testing support, and generation of technical documentation. The second variable was oriented to measuring the perception of improvement in internal processes, reduction of times, automation of tasks, and agility in the delivery of technological products. The third variable evaluated aspects related to reduction of errors, improvement of team performance, precision in technical activities, and perception of work productivity.

For data collection, a structured survey consisting of 18 items was used, distributed across 3 main dimensions. Each variable was represented by six items, written in affirmative form to facilitate participants' assessment. The instrument used a 5-level Likert scale: 1 = strongly disagree, 2 = disagree, 3 = neither agree nor disagree, 4 = agree, and 5 = strongly agree. This scale allowed quantifying the degree of acceptance of workers regarding each statement related to the use of artificial intelligence and its impact on software engineering processes.

Before final administration, the instrument underwent a content review by three specialists in software engineering, technology management, and quantitative research. This validation made it possible to verify the clarity, relevance, and coherence of the items in relation to the proposed variables. Subsequently, a pilot test was administered to 18 workers with characteristics similar to those of the main sample, in order to identify potential comprehension difficulties and estimate the internal consistency of the questionnaire. As a result, a Cronbach's alpha coefficient of 0.87 was obtained, a value that demonstrated adequate reliability for the application of the instrument.

Data collection was carried out through a digital form, shared with workers in technology companies and systems areas of the 3 selected countries. Participants were informed about the academic objective of the study, the voluntary nature of their participation, and the confidential treatment of the data. No names, identity documents, or sensitive information that could directly identify the respondents were requested. Incomplete or duplicate responses were excluded before statistical processing.

The data analysis was conducted using descriptive and inferential statistics. First, results were organized using frequencies, percentages, means, and standard deviations, in order to describe the general behavior of each variable.

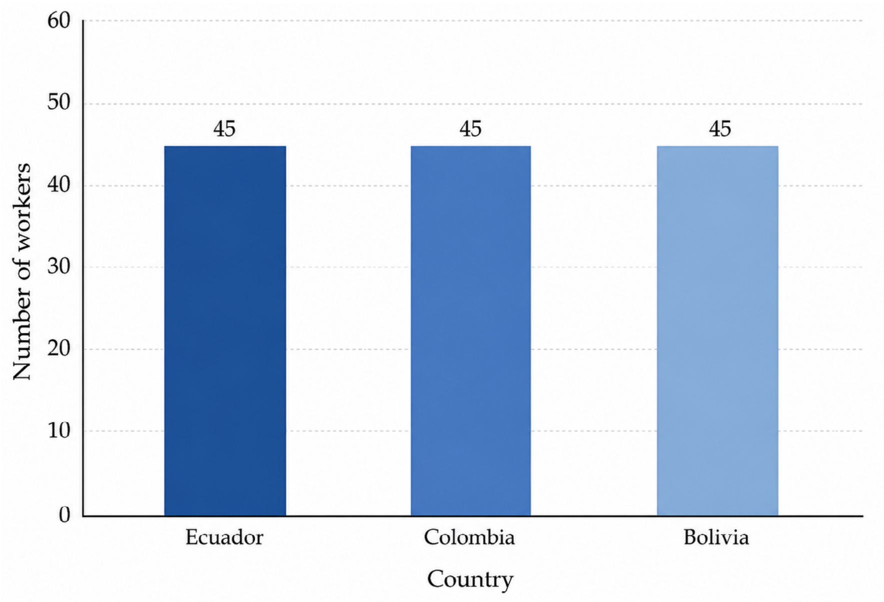
Subsequently, the Kolmogorov-Smirnov normality test was applied, considering the sample size. Because the data came from an ordinal Likert-type scale, the Spearman correlation coefficient was used to determine the relationship between the application of artificial intelligence, process optimization, and software quality/productivity.

For the interpretation of the results, a significance level of 0,05 was considered. The correlation values were analyzed according to their direction and intensity, which made it possible to establish whether the relationships between variables were positive, negative, weak, moderate, or strong. Finally, the data were organized into statistical tables to facilitate the presentation of the findings and their subsequent comparison with previous studies in the discussion section.

RESULTS

The results show a favorable assessment of the application of artificial intelligence in software engineering processes. The majority of surveyed workers perceived that AI-based tools contribute to reducing operational times, automating repetitive activities, and improving the quality of technical work. In general terms, the three variables analyzed presented means higher than 4.00 on a scale of 1 to 5, indicating a positive trend in the responses.

Figure 1. Distribution of surveyed workers by country



Note. Proportional sample among Ecuador, Colombia, and Bolivia, with 45 workers. Own elaboration.

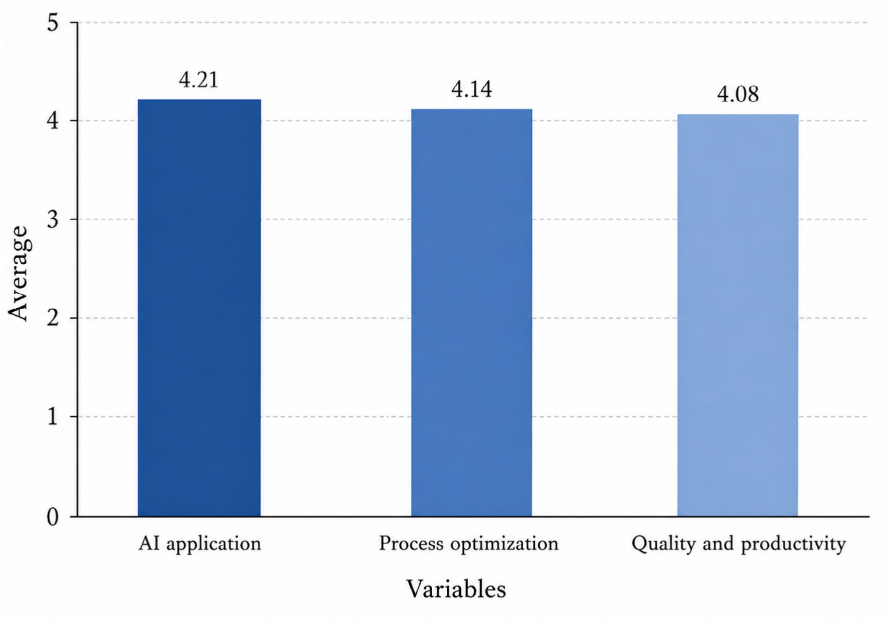
The sample was distributed proportionally among the three countries considered. Ecuador, Colombia, and Bolivia each recorded 45 workers, which allowed maintaining balance in the representation of participants and comparing perceptions without excessive concentration in a single national context.

Table 1. Descriptive statistics of the study variables

Variable	Mean	Standard deviation	Perception level
Application of artificial intelligence	4,21	0,61	High
Optimization of software engineering processes	4,14	0,64	High
Software quality and productivity	4,08	0,67	High

Note. Means and standard deviations summarize the behavior of variables. Authors' own elaboration.

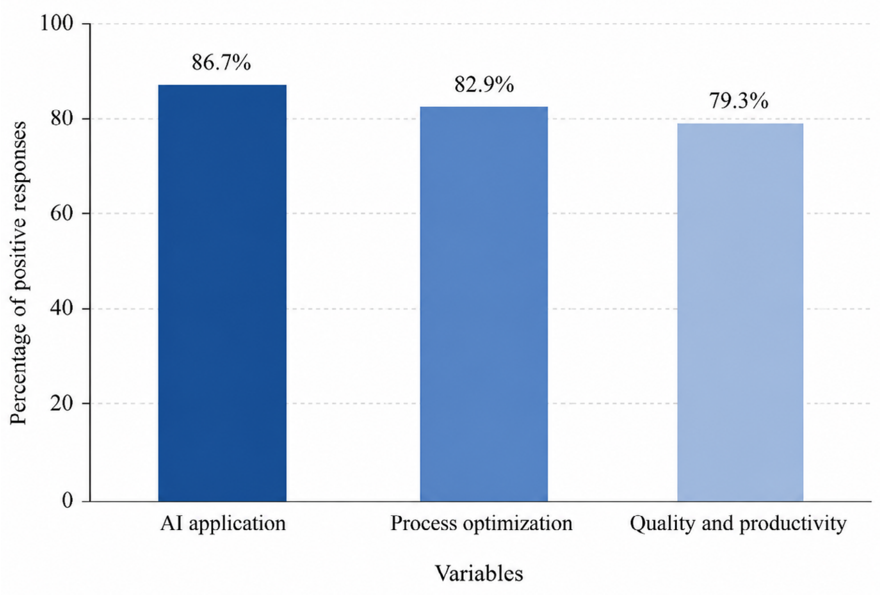
Figure 2. Overall average per variable



Note. Likert averages calculated from surveyed participating workers in three countries. Own elaboration.

The data from Table 1 show that the variable with the highest mean was the application of artificial intelligence, with a value of 4.21. This result indicates that workers recognize a growing use of AI tools in activities such as programming support, information analysis, testing, and technical documentation. Process optimization obtained a mean of 4.14, reflecting a positive perception of time reduction, task automation, and improved activity management. For its part, software quality and productivity reached a mean of 4.08, evidencing that participants also perceive improvements in error reduction and team performance.

Figure 3. Positive perception by variable



Note. Positive responses grouped between agree and strongly agree. Own elaboration.

Figure 2 shows that the three variables maintain values close to each other, although the application of artificial intelligence has a slight advantage over the others. This suggests that workers first identify the presence or use of intelligent tools, while the effects on optimization and productivity are perceived as progressive consequences of such application. Although the differences are not large, the results show a coherent relationship between the use of AI and the improvement of technical processes.

Figure 3 shows the percentage of participants who selected the options "agree" and "strongly agree" on the items associated with each variable. 86.7% of the workers expressed a positive perception regarding the application of artificial intelligence in their work activities. Likewise, 82.9% considered that AI favors the optimization of software engineering processes, while 79.3% indicated that it contributes to improving software quality and productivity. These values confirm a broad acceptance of AI as a support tool within the technological environment.

Regarding the inferential analysis, a positive and significant correlation was identified between the application of artificial intelligence and the optimization of software engineering processes. The Spearman coefficient was 0.68, with a significance level of $p < 0.05$, indicating a moderate-high positive relationship. Similarly, the relationship between application of artificial intelligence and software quality/productivity presented a coefficient of 0.63, also significant. Finally, the relationship between process optimization and quality/productivity reached a value of 0.71, evidencing the strongest association of the study.

These results allow us to affirm that, the greater the application of artificial intelligence in activities related to software engineering, the greater the perception of optimization in processes and improvement in the quality/productivity of the developed product. The highest correlation between process optimization and quality/productivity indicates that the benefits of AI are not limited to the use of digital tools, but are mainly reflected when they manage to be effectively integrated into the technical, operational, and organizational activities of software development.

DISCUSSION

The study findings show that the application of artificial intelligence is positively associated with the optimization of software engineering processes and with the improvement of software quality/productivity. This relationship confirms that AI should not be understood solely as an automation tool, but as a resource capable of intervening in technical, operational, and analytical activities within the development cycle. In this sense, the results coincide with De Silva and Alahakoon (1), who argue that artificial intelligence requires progressive integration within organizational processes to generate value from planning to production.

The correlation identified between AI application and process optimization supports the point made by Fan et al. (14), who explain that artificial intelligence can strengthen parameter generation, model formulation, and decision-making oriented toward process improvement. In the context of software engineering, this is reflected in the reduction of repetitive tasks, the automation of reviews, and the ability to anticipate problems before they affect product development. Therefore, AI provides greater efficiency when integrated into defined processes rather than when used in isolation or on an ad hoc basis.

In relation to software quality, the results are consistent with Al-Smadi et al. (21), who demonstrated that interpretable machine learning models can contribute to reliable defect prediction. Likewise, Daza et al. (22) highlight that defect prediction through AI is among the most relevant industrial applications for improving software reliability. This suggests that the positive perception of workers regarding quality/productivity is due not only to greater work speed, but also to the ability to detect errors, prioritize corrections, and improve the stability of developed products.

Similarly, the results are related to Esposito et al. (23), who point out that artificial intelligence can support the automatic analysis and reporting of software defects. This agreement is important because it demonstrates that AI can contribute not only to fault detection, but also to the generation of useful information for technical decision-making. Consequently, its value is strengthened when it transforms data from the development process into concrete actions to improve quality control.

The favorable perception of optimization is also related to advances in test automation tools. García et al. (24) argue that test automation with tools such as Selenium continues to be a key component in improving verification processes. Although traditional automation does not always involve artificial intelligence, its integration with intelligent models can expand the ability to detect errors, execute repetitive tests, and reduce validation times. This helps to explain why surveyed workers positively value the contribution of AI to technical software processes.

On the other hand, the relationship between AI and agile methodologies coincides with Ismail (25), who identifies that the integration of artificial intelligence into agile practices can facilitate planning, monitoring, and adaptation of development teams. In this study, the positive perception of process optimization can be explained by the ability of AI to support activities such as task prioritization, time estimation, technical documentation, and requirements analysis. In this way, AI can complement organizational agility without replacing the team's human coordination.

The results also align with the proposals of Banh et al. (8), who state that generative AI is transforming software engineering through coding assistants, documentation support, and the generation of technical solutions. This transformation may explain the high rating obtained for the AI application variable, as workers often perceive immediate benefits when intelligent tools reduce operational burden and accelerate routine tasks. However, this contribution must remain under professional supervision, because AI-generated results require technical validation and human judgment.

From a productivity perspective, the findings coincide with Czarnitzki et al. (3), who show that artificial intelligence can be related to improvements in productivity at the firm level. In the present study, this relationship is observed in workers' perception of improved technical performance and reduced time in development activities. However, productivity should not be interpreted solely as greater speed, but rather as a combination of efficiency, precision, reduced rework, and better use of available resources.

Finally, the results align with Meza Terbullino et al. (9), who propose that the integration of artificial intelligence into engineering processes requires critical analysis, training, and implementation criteria. Although the data reveal a favorable perception, the adoption of AI also implies challenges related to tool reliability, technological dependence, data protection, and the need to strengthen digital competencies in teams. Therefore, the optimization of software engineering processes through AI must be approached as a strategic, gradual, and continuously evaluated process.

Overall, the discussion allows us to affirm that artificial intelligence has a positive impact on the optimization of software engineering processes when integrated into specific development, testing, management, and quality control activities. However, its effectiveness depends on how organizations incorporate these tools, train their workers, and maintain human validation mechanisms. Thus, AI does not replace the professional role of the software team, but rather expands its capabilities to work with greater efficiency, precision, and orientation toward continuous improvement.

CONCLUSIONS

The application of artificial intelligence in software engineering processes was perceived favorably by the surveyed workers, providing evidence that these tools have become relevant support for technical activities such as assisted programming, information analysis, documentation, and error review. This demonstrates that AI not only facilitates operational tasks but also strengthens decision-making within software development.

Process optimization showed a positive relationship with the use of artificial intelligence, especially regarding time reduction, automation of repetitive tasks, and improvements in work organization. These results allow us to conclude that AI can contribute to development teams working with greater agility, reducing rework, and managing software lifecycle activities more efficiently.

Software quality and productivity also received a high rating, indicating that artificial intelligence can contribute to early defect detection, quality control, and enhanced performance of technological teams. In this sense, its incorporation improves not only work speed but also the precision of processes and the reliability of developed products.

The implementation of artificial intelligence in software engineering must be carefully planned, taking into account staff training, human validation of the results, and ethical control of the use of these tools. Therefore, AI must be understood as a complementary resource that enhances professional capabilities but requires supervision to avoid technological dependence, undetected errors, or automated decisions without technical criteria.

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CONFLICT OF INTEREST

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