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A SOFTWARE ARTIFACT FOR THE RAPID OPTIMIZATION OF LLMS IN THE SOFTWARE DEVELOPMENT LIFE CYCLE

UN ARTEFACTO DE SOFTWARE PARA LA OPTIMIZACIÓN RÁPIDA DE LLMS EN EL CICLO DE VIDA DEL DESARROLLO DE SOFTWARE

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Resumen-- La inteligencia artificial (IA) desempeña un papel fundamental en el desarrollo de software moderno, transformando significativamente el diseño, la escritura, las pruebas y el mantenimiento del código por parte de los desarrolladores. En la actualidad, programadores de distintos niveles han integrado herramientas basadas en IA en diferentes fases del ciclo de vida del desarrollo de software (SDLC), desde la generación de código hasta la implementación. Este estudio analiza el impacto de estas tecnologías en la práctica profesional, identifica las herramientas más utilizadas y propone las mejores prácticas para la adopción responsable de la IA, con el objetivo de optimizar su implementación de manera eficiente y ética. Como parte de este estudio, se desarrolló un artefacto metodológico para guiar la formulación estructurada de indicaciones, que funciona como un modelo para mejorar la precisión y la utilidad de los resultados generados por la IA. Este artefacto se validó a través de tres casos de uso de prueba de concepto (consultas SQL, desarrollo de backend e implementación en AWS), lo que demostró su potencial como base de conocimientos para los equipos que buscan incorporar herramientas de IA de forma sistemática en sus flujos de trabajo.

Palabras clave-- Artefacto, desarrollo de software, herramientas, indicaciones, inteligencia artificial, programadores.

Abstract-- Artificial Intelligence (AI) plays a key role in modern software development, significantly transforming developers' design, writing, testing, and maintaining their code. Currently, programmers at various levels have integrated AI-based tools into different phases of the software development life cycle (SDLC), from code generation to deployment. This study analyzes the impact of these technologies on professional practice, identifies the most used tools, and proposes best practices for the responsible adoption of AI, aiming to optimize its implementation efficiently and ethically. As part of this study, a methodological artifact was developed to guide the structured formulation of prompts, functioning as a model to enhance the precision and utility of AI-generated outputs. This artifact was validated through three proof-of-concept use cases (SQL queries, backend development, and deployment in AWS), demonstrating its potential as a knowledge base for teams seeking to incorporate AI tools systematically into their workflows.

Keywords-- Artifact, artificial intelligence, software development, prompt, programmers, tool.

INTRODUCTION

In the era of AI, software developers began to integrate multiple AI-based tools into various phases of the Software Development Life Cycle (SDLC) [1,2]. These applications include

automatic code generation, assistance in writing technical documentation, review, analysis, and error detection; enabling them to optimize development time, automate tasks, and increase the quality of final products. This trend represents a new paradigm in software engineering, where the traditional human-centered method is being renewed to collaborate with intelligent agents [3].

Currently, tools such as GitHub Copilot, Amazon CodeWhisperer, Tabnine, DeepCode, Amazon CodeGuru, IntelliCode, and even ChatGPT and Gemini represent a new form of collaboration between humans and language models [4,5]. These innovative tools stand out for reducing code errors, increasing production speed, and generating robust solutions according to various studies [6].

As a special case, ChatGPT, Copilot, and Gemini have demonstrated in recent years that they are versatile tools that can help developers not only with programming tasks but also with understanding requirements, generating examples, optimizing code, and explaining complex concepts in natural language [4,5,]. However, despite their growing adoption, there are currently no formal guidelines to guide developers make optimal use of them, nor universal standards that guarantee the quality and ethics of the results obtained with these technologies. In consequence, adopting these tools and obtaining the greatest benefits depends on technical, organizational, and human factors [7].

In this context, this article aims to analyze the best ways to integrate Artificial Intelligence into the software development life cycle, considering both its capabilities and current limitations. The purpose of this reflection is to contribute to the formulation of a strategic and sustainable approach that allows maximizing the potential of AI without compromising the integrity of the software engineering process or the quality of the products generated. To achieve this, 150 active software engineering professionals were surveyed, including those working in the public sector, private sector, freelancers, programming teachers, IT professors, and professionals in the technology sector in general. The survey results made it possible to identify the most used tools in the software development life cycle. Based on this analysis, a method and a software artifact were designed to guide in the optimize creation of requests through prompts. This artifact was adapted through proof-of-concept testing, of which three implementations are presented in this article, corresponding to SDLC phases: data modeling, code generation, and production deployment of applications. The results were significantly satisfactory, achieving 90% effectiveness in integrating AI-based solutions into the SDLC.

The article is organized as follows: Section 2 presents the motivation for this study; Section 3 describes related work that defines the state of the art; Section 4 explains the methods and materials used for data collection and analysis, as well as the design of the artifact for prompt optimization; Section 5 presents the analysis of results and the practical implications of the proof-of-concept tests; and finally, Section 6 summarizes the conclusions, recommendations, and proposals for future studies.

MOTIVATION

Software development is among the professions and industries revolutionized by AI tools. These tools include solutions to modernize the software engineering process in a hybrid way; that is, programmers stand in the need to incorporate innovative methods to improve their productivity. In this context, artificial intelligence emerges to transform the software engineering process, but its adoption requires more than just using support applications, it involves developing a new collaborative work culture that employs ethical solution in the generation of management methods; formalizing frameworks and workflows, organizing knowledge management in development environments, and understanding how, when, and which tools to apply within the SDLC [8].

From an educational perspective, universities being the main institutions that train programming professionals, need to understand methods for adopting AI tools that teachers can integrate into their daily teaching. These methods are often difficult to identify because they are empirical and software companies adapt them during their processes. On the other hand, it is observed that engineering students use AI tools inappropriately when solving programming problems. This situation justifies the need for a formal method or guideline that allows them to use the tools correctly while also improving their learning.

From a technological perspective, self-taught junior programmers and future professionals in the software industry often don't have full access to the methods used by some companies to integrate AI into software development across different SDLC phases. This highlights the need for studies focused on the appropriate use of AI tools.

From an industrial perspective, freelancers and small, medium, and large software companies around the world, continue integrating innovative AI methods and techniques into their workflows based on their own experiments. However, those who have not yet done so may lose time, limit quality development, or even lose money while trying to perfect this collaboration with LLMs. For this reason, this study is justified.

Finally, this study aims to contribute to the development of methodological strategies for programmers, researchers, and software engineering companies that facilitate the progressive and sustainable integration of AI tools into the SDLC. It seeks to help them manage prompt requests across various LLMs they use, while also enabling them to maintain a knowledge base of prompts applied at different development phases, with the purpose of reusing these artifacts in multiple solutions.

RELATED WORKS.

Traditionally, the field of software development has been traditionally dominated by human logic, experience, and structured reasoning. However, with significant technological advancements in recent years and the exponential emergence of AI, this discipline has begun to integrating automated models to assist programmers with simple tasks.

Despite this remarkable accomplishment of Goostman's development team and the milestone in passing the famous Turing test, the reaction of the scientific community was not unanimous. One of the most significant contributions comes from researchers [9] who introduced Codex, the foundational model behind the GitHub Copilot. This model, trained in vast amounts of source code, demonstrated the ability to automatically generate code in various programming languages, addressing tasks ranging from simple to complex. The study evaluated its efficiency through competitive programming tests and found that Codex solved approximately 37 % of the presented problems, highlighting its potential as a developer assistance tool, although with notable limitations in understanding deep semantics.Another relevant study [10], compares several automatic code completion tools based on language models, including Copilot, CodeWhisperer, and Tabnine. Their study revealed significant differences in accuracy, contextual comprehension, and compatibility among different programming languages. This comparison showed that although these tools share a common purpose, their effectiveness varies considerably depending on the development environment, type of task performed, and programmer experience level.

On the other hand, in 2023 [11], presented a research study focused on analyzing the most frequent errors made by language models in code generation. The study concluded that although tools like Copilot or ChatGPT can be helpful, their outputs must be critically evaluated to avoid structural and logical mistakes. Additionally, organizations such as the OECD [12] and IEEE have proposed classification frameworks aimed at ensuring transparency, traceability, and accountability in AI-based systems, which are useful for evaluating the role of tools such as ChatGPT within the software development life cycle.

In 2023 [13], presented a study focused on identifying best practices and AI tools integrated into the different phases of the software development life cycle (SDLC), including design automation, code review, and implementation. The research highlighted that incorporating AI techniques improves productivity and software quality through automated analysis and intelligent support during system development. In 2024, the study "Heuristics applied in artificial intelligence, a systematic review" [14] aimed to analyze the role of heuristic methods in optimizing artificial intelligence processes. This work identifies how these strategies contribute to improving the efficiency and accuracy of intelligent models in various areas of technological development. This approach is relevant to the present study, as it coincides with the search for mechanisms that allow for a more efficient and structured use of artificial intelligence within the software development life cycle. In 2024, Sajja and Thakur presented the study "Integrating Generative AI into the Software Development Lifecycle: Impacts on Code Quality and Maintenance" [15], in which they analyze the incorporation of generative artificial intelligence tools throughout the different phases

of the software development lifecycle. Their research highlights how AI can support processes such as code generation, automated documentation, and early error detection, helping to improve the efficiency and quality of the final product. The authors also emphasize the challenges related to dependence on these tools, validation of the results obtained, and interpretation of the solutions generated.

Taken together, these studies show that the use of AI in software development is both viable and an expanding reality. However, these studies agreed that its implementation must be accompanied by validation criteria, human review practices, and ethical considerations. This article differs from previous works in that it not only reviews current AI applications, but also proposes concrete strategies for their optimal use, addressing both their potential and limitations from a critical, evidence-based perspective.

MATERIALS AND METHODS

This study was structured into four phases, as shown in Figure 1. In the Investigate phase, a set of items was designed for the data collection instrument. These items were developed based on the phases of the SDLC, as well as the dependent and independent variables of the case study. The Analysis phase allowed us to identify the maximum and minimum values in the collected data, thus facilitating a more precise interpretation of the results. Subsequently, the Implementation phase consisted of experimenting with the initially identified AI tools. Finally, in the Generate phase, the best practice model was developed for the appropriate use of Artificial Intelligence across the different phases of the software development life cycle.

Figure 1. *Defined phases of the study methodology.*

Source. *Own elaboration (2026).*

Investigate Phase

During the research phase, the most representative phases in the software development process were modeled, based on established theoretical frameworks [1,2]. Figure 2 presents a schematic representation of these phases highlighting where AI can have a major impact or is already being actively applied.

Figure 2. *Most well-known phases of software development.*

Source. *Own elaboration (2026).*

Subsequently, the study's research variables [16, 17] were established and organized into five thematic categories for analytical purposes: participant profile, technical specialization, use of AI tools, risk perception, and regulatory considerations, as shown in Table 1.

Table 1. *Description of the study variables applied.*

CATEGORY	VARIABLE	PURPOSE
Participant Profile	Age Group, Geographical Location, Professional Status, Years of Experience	Characterize the participants based on their background, experience and context.
Technical Specialization	Area of Development	Analyze how the area of technical focus relates to the use of AI
AI Tools	Frequency and confidence in AI generated Code	Understand actual practices and validation of AI-generated code.
Risk Perception	Perceived risks associated with AI use	Identify key ethical, technical, and professional concerns
Regulatory Perspective	Option on intellectual property legislation	Assess the perceived need for legal frameworks and regulatory guidelines.

Source: *Own elaboration (2026)*

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Finally, the items that made up the results-obtaining [18, 19] device were written, that is, the applied questionnaire. To ensure coherence and validity, the questions were inspired by instruments previously validated in related research studies [20, 21]. Each question was carefully designed to be clear and understandable to participants.

The questionnaire included closed-ended and multiple-choice questions [22], enabling quantitative analysis of the data [23]. Standardization of the artifact also ensured that each item was directly linked to a specific variable and corresponded to a particular phase of the software development process, thus facilitating subsequent analysis and interpretation.

Analysis Phase

In the second phase, a data collection instrument was used (survey). This collection was carried out online through Google Forms [24, 25], ensuring access to a diverse sample of participants both nationally and internationally.

The questionnaire was developed based on the variables defined in the research phase (participants' profile, technical specialization, AI tools, risk perception, and regulatory perspective), which are directly related to the study's objectives.

Each group of questions was designed to characterize the participants' profiles, analyze their practices in using artificial intelligence (AI) during different phases of the software life cycle, and identify perceptions of risk, trust, and regulatory perspectives regarding the use of generative AI tools.

The questions included closed-ended and multiple-choice items, with frequency, single, or multiple selection scales, depending on the type of variable evaluated. The results obtained from the survey can be found in the results section.

The instrument was applied to a total of 200 people divided into two groups:

- 150 active professionals in the software development field, with work experience in various sectors and regions of the country.
- 50 programming students from the state of Tabasco, Mexico.

Responses from the second group came from various states, highlighting the state of Tabasco (55.5 %) and Mexico City (10.5 %) having the highest participation (Figure 3).

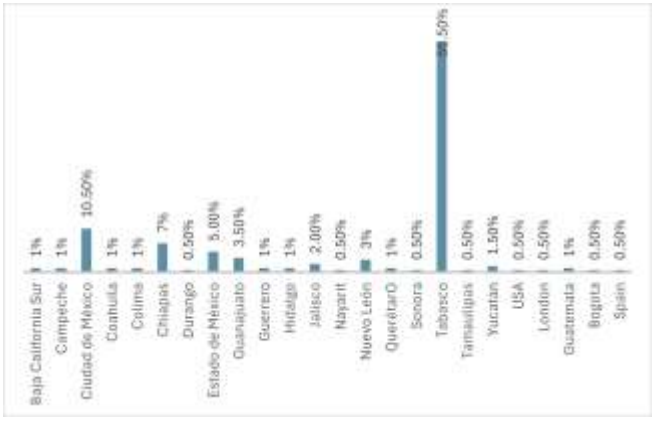


Figure 3. *Geographical location.*
Source. *Own elaboration (2026).*

Implementation Phase

Based on the analysis carried out in this phase, a standardized instrument was designed to optimize the use of artificial intelligence tools in software development.

In the context of AI-assisted software development, the way developers formulate their requests, also known as prompts [26,27], is a determining factor for obtaining useful, accurate, and coherent results. Unlike other automated tools, language models such as ChatGPT, Gemini, and Copilot (to name a few), do not infer user intentions; instead, they interpret the instructions contextually. Consequently, vague, incomplete, or poorly structured prompts may lead to inaccurate or inapplicable responses. By contrast, clear, detailed, and contextualized prompts significantly increase the effectiveness of the language model's response [28].

In this regard, a set of recommendations and criteria are presented to improve communication with language models in a standardized artifact, thereby facilitating efficient integration into different phases of software development.

Rather than functioning merely as a documentation format, this tool acts as a strategic asset that helps translate development needs into technically detailed instructions for a language model.

The implementation of this artifact aims to ensure that, during system development, the control of the phases where AI was used and how it was applied is documented, in order to promote a responsible, ethical, and verifiable use of AI within software engineering processes.

The structure used in the User Stories format [29, 30] employed in agile methodologies was taken as a reference for the design of this format. This model served as the basis for defining the fields of the artifact, allowing us to clearly record the stage of the software life cycle where it is being implemented, the tool used, the expected outcome, the context of the case, and the prompt applied.

The goal of the tool is to guide developers in formulating effective prompts and document the process through a series of questions that allow them to properly structure their requests to the language model. Among the main questions that guide its application are:

- What am I doing?
- What do I need to accomplish with AI?
- What attributes or details should the expected solution include?
- What environment, technologies, or languages am I using?
- What architecture, pattern, or file structure does the solution require?
- What exactly should the expected result do?

Table 2. *Generated artifact for the creation of structured prompts*

ARTIFACT FOR THE PROMPT			
Artifact ID	#	**Case Study**	#
Author	Name	**Date**	DD/MM/AAAA
General Context	What am I working on?		
Phases of SDLC	Where am I in the development process?		
Specific Context	What do I need to perform?		
Data Source	Relevant input structure (attributes, variables, data type, etc.).		
Technology Stack	Stack of technologies being implemented.		
Output Format	Element that I require to generate with the IA according to the development environment used (files, classes, methods, functions, JSON, XML, etc.).		
Functional Requirement	Methods to integrate, functions, etc. In this section the user must be very specific as to what is required, explaining in detail what the AI is required to do.		
Language Model Instruction			
Concrete and structured formulation of the request to be sent to the linguistic model based on the above attributes, considering a detailed and step-by-step structure for best results.			

Source. *Own elaboration (2026).*

This structure made it possible to translate complex needs into understandable, specific, and functional prompts [5, 31] for the AI in use. Its implementation aims to reduce ambiguity in interactions with AI models while also improving developer productivity and fostering continuous learning when working with intelligent systems. To validate the usefulness of the designed artifact, three real use cases related to common software development tasks were applied.

Proof of concept 1.

The first case illustrates how AI can be optimized to generate data queries in a database in PostgreSQL involving specific data from several interrelated tables. This scenario involves an academic system that manages student payments across different educational programs. The objective is to obtain a functional SQL query that retrieves payment information for students, displaying only those payments whose status is "Validated" or "Under Review."

This test aimed to assess the accuracy of the model in handling table relationships, applying conditional filters, and generating an output format aligned with real system requirements.

Table 3. *Artifact for generating SQL queries.*

ARTIFACT FOR PROMPT			
Artifact ID	001	**Case Study**	A001
Author	Vania Méndez	**Date**	06/04/2025
General Context	I'm developing a database that keeps student payments		
Phases of SDLC	Data Base		
Specific Context	I need to retrieve students enrolled in a specific academic program, including only payments that are validated or in process.		
Data Source	Schema for tables student, payment, payment_status, payment_type and program		
Technology Stack	PostgreSQL		
Output Format	SQL Query		
Functional Requirement	The query must be returned to the student's code, full name, program name, payment amount and date, only for payments where the status is "validated" or "under reviews".		

Language Model Instruction
I have a PostgreSQL database with the following tables: • Student (id, code, name, lastname, picture, gender_id, program_id) • Payment (id, student_code, date, type_id, status, amount, file) • Payment_status(id, status) • Payment_type (id, name) • Program (id, code, name, description) I need a SQL query to retrieve students enrolled in a specific program, including their payments that are either "Validated" or "Under Review". The result must show the student code, full name (concatenation of name and lastname), program name, payment type, payment amount, and payment date. The query must use JOINs to reflect the key foreign relationships, exclude payments with any other status, and be filtered by program.

Source. *Own elaboration (2026).*

Proof of concept 2

The second functional case (Table 4) was developed for the coding phase, where we sought to solve a common need in backend projects, the registration of a user with file upload in an application developed in SpringBoot.

The general context involved the development of a school tracking system, with data persistence in a PostgreSQL database and access through JPA [32], where the creation of the necessary code sections to list the registered students and the registration module of a new student following the SpringBoot structure is required. Based on this requirement, the artifact is structured to capture the request in a clear and complete manner, detailing the required structure for each requested file.

Table 4. *Artifact for a service in Spring Boot.*

ARTIFACT FOR PROMPT			
Artifact ID	002	**Case Study**	A002
Author	Bryan Scott	**Date**	05/04/2025
General Context	I am developing a school payment control system with Spring Boot.		
Phases of SDLC	Coding / Backend Implementation		
Specific Context	I need to implement backend logic to register a new student, save a photo of them, and query students using code.		
Data Source	Student Entity whit fields: id, code, first name, last name, program (FK to program Entity, stores program code), gender (FK to gender Entity) and picture saved in resources/images		
Technology Stack	Spring Boot as development environment, PostgreSQL as data access technology, JPA and library MultipartFile.		
Output Format	Repository, Service and REST Controller classes.		
Functional Requirement	Repository with method to find student by code, Service that saves student info and stores uploaded image via MultipartFile, Controller with: POST to register a new student and GET to retrieve students by code.		
Language Model Instruction			
I am developing a school tracking system with Spring Boot; the information is stored in a PostgreSQL database and JPA is used for data access. I already have the entity “Student” with the structure: id, code, first name, last name, program, gender and photo of the student. The program field is a foreign key to the program entity and when storing a student, the program code must be entered. The gender field is a foreign key to the gender table. The ID field is a self-incrementing field in the database. I require: The creation of the project repository with a method to search for students by code. A service that saves the information of a new student based on the entity structure created, the student image will be saved in the project path resources/images and you must implement MultipartFile. A controller with a POST endpoint to receive the student's data based on the created service, and a GET endpoint to search for students by their code. The code should be ready to be tested in Swagger.			

Source: *Own elaboration (2026).*

Proof of concept 3.

The third case study focused on evaluating the use of artificial intelligence as a key assistant in the complete configuration and deployment of a backend application developed with SpringBoot on an AWS web server.

This case represents a realistic scenario in which a programmer needs to deploy a project in the cloud, starting from covering everything from domain configuration to production deployment and verification using Swagger.

Table 5. *Artifact for web application deployment.*

ARTIFACT FOR PROMPT			
Artifact ID	003	**Case Study**	A003
Author	Joseph McAllen	**Date**	06/04/2025
General Context	I have a backend application developed in Spring Boot 3.4.6, with Maven 4.0.0.		
Phases of SDLC	Deployment		

Specific Context	I need to configure the complete deployment of the application in AWS, from domain configuration to EC2 setup and final Swagger test.
Data Source	The application is a .jar file located in a local folder. Uses PostgreSQL 16 as DB and needs to be deployed behind NGINX in an EC2 instance with Amazon Linux 2023.
Technology Stack	Spring Boot 3.4.6, Maven 4.0.0, Java JDK 21, PostgreSQL 16, AWS EC2, Amazon Linux 2023, NGINX, WinSCP
Output Format	Step-by-step instructions for, AWS domain and DNS configuration, EC2 provisioning, Software installation, Project upload and execution, NGINX reverse proxy Domain linkage and Swagger UI access
Functional Requirement	The system must be deployed successfully and made accessible via a custom domain name (chatgpt-prompt-model.com) through HTTPS and tested via Swagger UI.
Language Model Instruction	
I have a backend application developed in Spring Boot 3.4.6, with Maven 4.0.0 and I need you to give me the steps for the configuration of its deployment contemplating: The detailed steps for creating a domain in AWS, which will be named chatgpt-prompt-model.com, integrates the configuration to obtain the elastic IP, enable port 8080 and type "A" records, one with www and the other with the IP address of the project. The detailed steps for the creation of a virtual machine in an EC2 instance with Amazon Linux 2023 where java with JDK 21, PostgreSQL in its version 16, NGNIX as a reverse server must be installed. The configuration must contemplate the creation of remote keys, enable access protocols by https, network configurations to connect from anywhere (SSH), integrates the steps for the configuration of the domain in NGNIX. The project folder is located locally, integrates the configurations to convert it to a .jar and the instructions to upload it from winscp to the virtual machine. To test the operation of the deployment, it should allow me to connect to Swagger UI to test my API.	

Source: *Own elaboration (2026).*

Results

This section presents the results obtained during the study, which are divided into two main sections.

The first part presents the results of the survey conducted among students and professors in the development area (established in the analysis phase), aimed at identifying the degree of adoption, perception, and use of artificial intelligence tools in the different phases of the software life cycle.

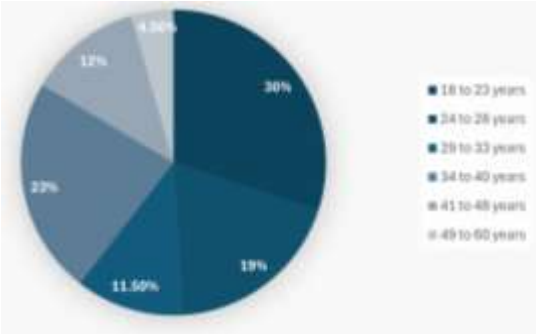
The second part shows the proof-of-concept tests of the standardized artifact, developed to validate its functionality and effectiveness for optimizing effective prompts for the implementation of AI tools during system development.

Survery Results

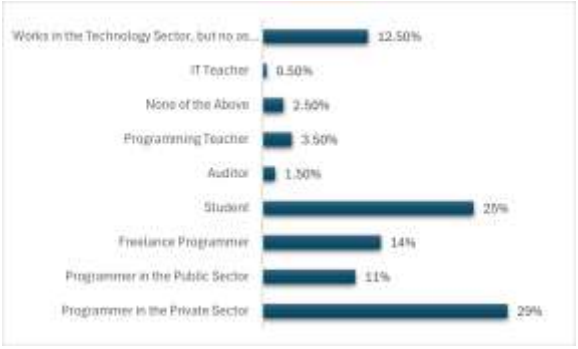
Participant Profile

The graphs in figure 4 show the age groups and professional status of the people surveyed. The graph (a) shows that the largest percentage of respondents (30 %) were in the age group of 18 to 23 years, followed by those aged 34 to 40 (23 %) and those aged 24 to 28 (19 %). This suggests that the use of AI tools is particularly prevalent among young adults.

The graphic (b) in Figure 4 shows that 29 % of respondents were developers in the private sector, 25 % were programming students, 14 % worked as freelancers, and 11 % were developers in the public sector.



(a)



(b)

Figure 4. *(a) Age range of participants; (b) Sector where the participants are located.*

Source. *Own elaboration (2026).*

Technical Specialization.

Figure 5 shows us the areas in which the surveyed developers were focused: 42.9 % were Full Stack developers, 21.8 % were backend developers, and 12.9 % specialized in database development and administration.

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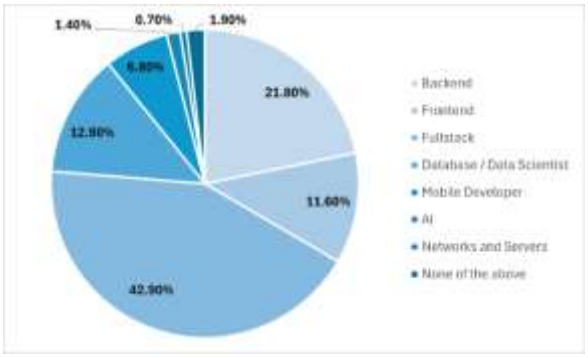
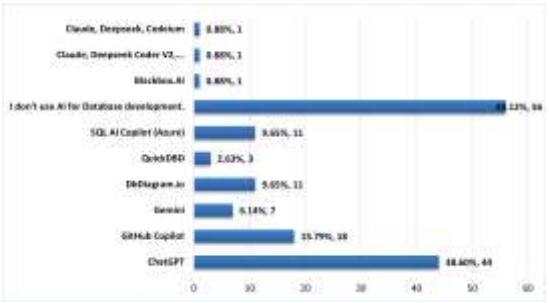


Figure 5. *Developers' area of expertise.*

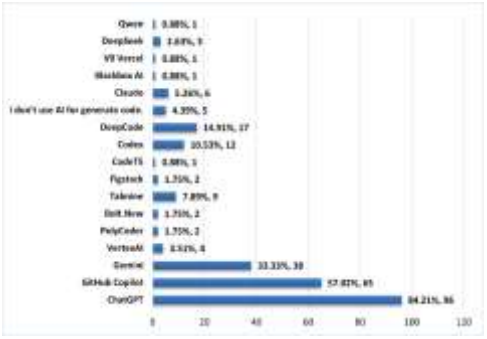
Source. *Own elaboration (2026).*

AI Tools.

Below are the results of the survey questions regarding the most used tools in each established development phase. Iti's important to notice that this section included multiple-choice answers, so that users could select more than one response.



(a)



(b)

Figure 6. *(a) Most commonly used tools during database schema generation and design; (b) most used tools in the coding phase.*

Source. *Own elaboration (2026).*

The graph (a) in Figure 6 shows that most respondents (49.12%) did not use AI tools for database development. Among those who do, ChatGPT was the most popular (38.6%), followed by GitHub Copilot (15.79%), DbDiagram.io, and SQL AI Copilot (9.65% each). This indicates a growing but still limited use of AI at this stage.

The graphic (b) in Figure 6 demonstrates that most respondents (84.21%) have adopted ChatGPT as a tool during the coding phase, followed by GitHub Copilot (57%) and Gemini (33.3%). Only 4.39% indicated they don't use AI tools for code generation.

Figure 7 shows the AI tools used during the error detection phase, where 64.91% of respondents use ChatGPT in this phase, followed by GitHub Copilot (40.35%) and Gemini (14%).

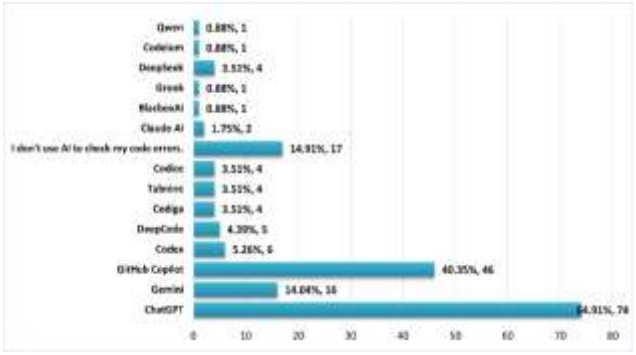


Figure 7. *Most commonly used tools during the error detection phase.*

Source. *Own elaboration (2026).*

Figure 8 shows that 79.6 % of respondents do not use AI tools during the deployment phase. However, among those who do, 13.16 % have implemented the use of GitHub Copilot for DevOps as a support tool.

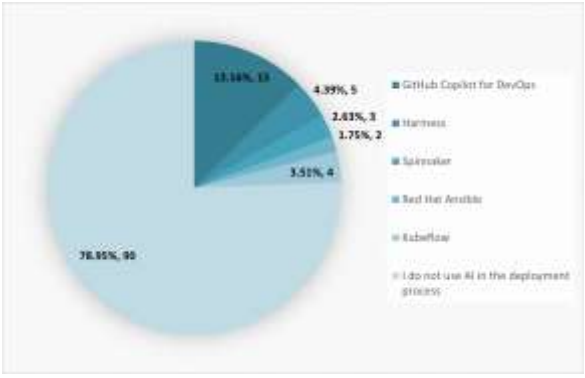
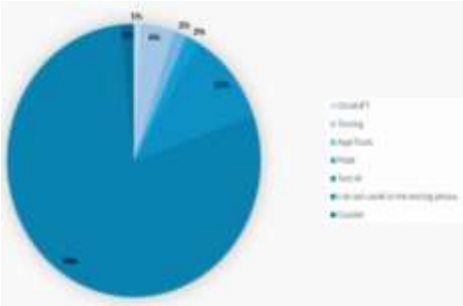
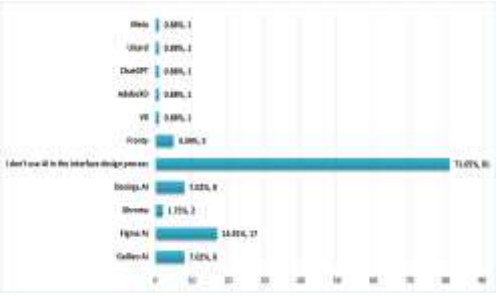


Figure 8. *Most commonly used tools in the deployment phase of a system.*

Source: *Own elaboration (2026).*



(a)



(b)

Figure 9. *(a) Most used tools during the testing phase; (b) Most used tools in interface design.*

Source. *Own elaboration (2026).*

Figure 9 section (a) shows that during the testing phase, most developers (80.7 %) did not use AI tools. Among those who do, Testa.AI (11.4 %) and Testim (4.39 %) are the most used.

For interface design section (b) in Figure 8 shows that, the majority of respondents (71.05 %) don't use AI tools. However, among those who do, FigmaAI is the most used (14.9 %), followed by Galileo AI and Designs AI (7.02 %).

Figure 10 shows that for the documentation phase in software development, 55.26 % of respondents don't use AI tools. On the other hand, 31.58 % indicated to use ChatGPT and 23.68 % use GitHub Copilot.

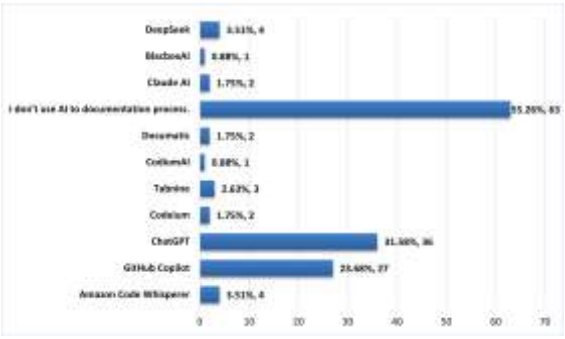


Figure 10. *Most commonly used tools for project documentation.*

Source. *Own elaboration (2026).*

Finally, in Figure 11 we can observe that regarding AI-generated code requests, 67.5 % of respondents review AI-generated code before using it, while 27.2 % trust the generated code but run tests prior to implementation.

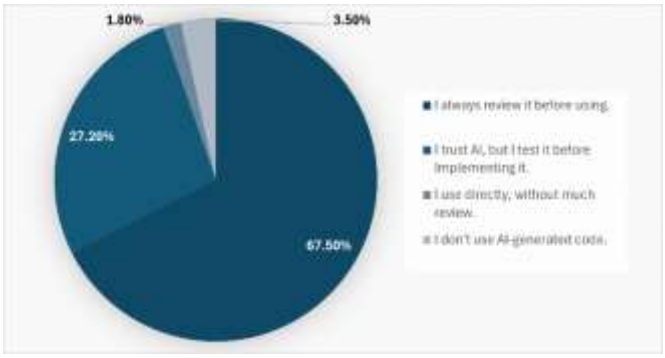


Figure 11. *Confidence in the results obtained by AI.*

Source. *Own elaboration (2026).*

Risk Perception.

All respondents were asked about the perceived risks of using AI in software development (Figure 12). The most significant concern (60 %) was the risk of over-dependence on the use of AI. Other risks mentioned included loss of creativity (16.5 %), potential production errors (14.5 %), and privacy issues (5 %). These results indicate that developers critically reflect on the implications of using AI for software development.

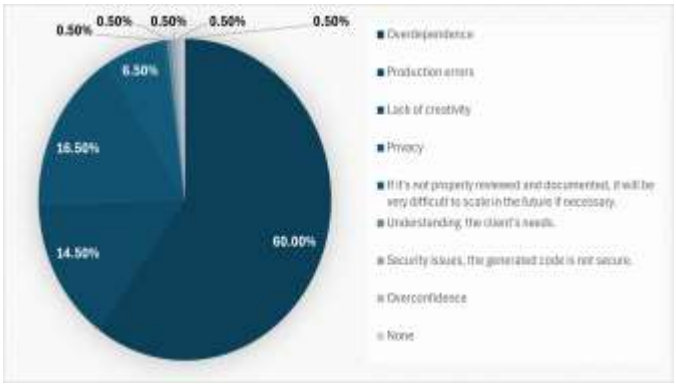


Figure 12. *Perception of the risk of AI implementation.*

Source. *Own elaboration (2026).*

Regulatory Perspective.

This section focuses on the ethical implications associated with AI implementation in software development. [30] It highlights the need for specific ethical considerations in the design, use,

and consequences of technologies, particularly in the era of Artificial Intelligence. Data privacy and equitable access are critical issues.

Regarding intellectual property, one question asked respondents whether they believed there should be laws or legislation regulating the ownership of the AI-generated code. More than half of the respondents (52.5 %) agreed that laws or legal definitions should clarify the legal ownership of AI-generated code. Meanwhile, 18.5 % believed that code generated by AI should not have authorship implications, 16.5 % considered copyright regulation unnecessary, and 12.5 % were uncertain about this approach (Figure 13).

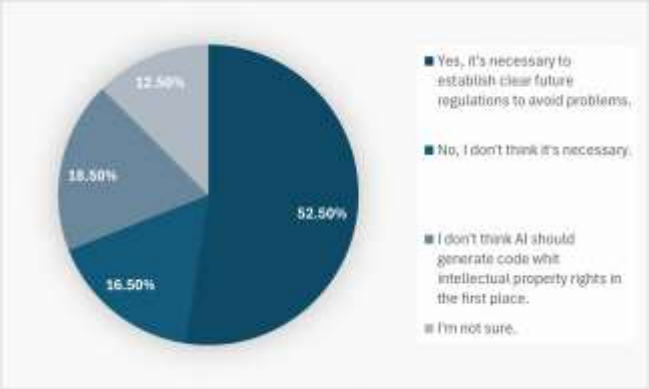


Figure 13. *Consideration of intellectual property laws*.

Source. *Own elaboration (2026).*

Regarding broader regulations on AI use, 38.5 % of respondents supported AI regulation due to potential risks to software quality, 20 % favored limited regulation, and 20.5 % believe AI tools should be treated like any other development tool (Figure 14).

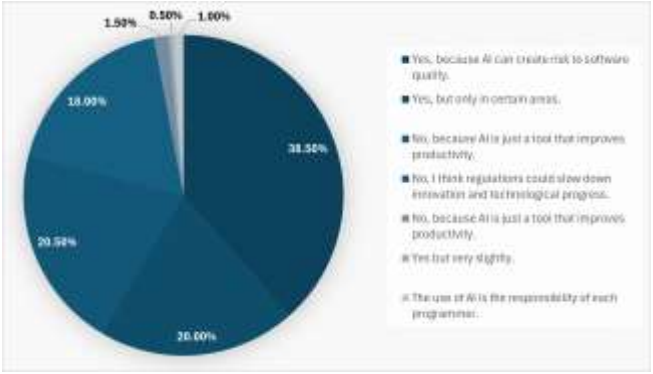


Figure 14. *Consideration of AI use regulations*.

Source. *Own elaboration (2026).*

The results revealed that the most widely used tool during the development phases included in the data collection artifact was the ChatGPT, particularly in the coding and error detection s0tages.

However, it's important to clarify that ChatGPT is not a specialized coding assistant nor a tool created exclusively for development field. ChatGPT is an AI-based language model trained on large volumes of text, including documentation, code, and technical conversations [33, 34], enabling it to simulate expert interactions in programming and other fields created by OpenAI, which ich also known as generative AI [35] because of its ability to produce original content.

Since its launch on November 30, 2022, ChatGPT has become the fastest-growing application in history, reaching 100 million active users just two months after its release [35]. ChatGPT operates using generative pre-trained transformers (GPT), a type of large language model (LLM). It relies on complex Machine Learning algorithms [37] that compare the user input with its pretrained data. The ChatGPT results were predictions based on the patterns learned the training.

Similarly, the results reflect the need for a regulatory framework for the implementation and use of AI in software development, which takes into account the diverse contexts in which these technologies are adopted.

While a significant portion of respondents supported formal regulation due to potential ethical and software quality risks, it is essential to acknowledge those who advocate for flexible, adaptive, and non-obstructive regulation. Allowing innovation and full exploitation of AI capabilities without unnecessary restrictions.

Generate Phase

The experimental tests of the proposed artifact were carried out using ChatGPT, a tool selected based on the survey results, which identified ChatGPT as the most widely used artificial intelligence across the different phases of the SDLC.

For the implementation of the case studies, the free version of ChatGPT 4.0 was used, executing each of the prompts designed in the instrument. Subsequently, to verify the consistency and stability of the results, the same tests were replicated using the paid version (ChatGPT Plus, model 4.0).

In both versions, the results obtained were identical in terms of content, coherence, and output structure, which allowed us to validate that the artifact maintains its effectiveness regardless of free access or subscription to the platform.

Each of these tests focused on a different phase of the development process: generating SQL queries, implementing backend code, and deploying the application in a production environment. The main objective was to guide users in formulating precise and complete prompts to optimize LLM model answers in each case. The following sections provide a detailed description of each test, including its development, the results obtained, and the technical considerations identified throughout the process.

Results of concept proof 1.

The first proof of concept aimed to evaluate ChatGPT's ability to generate SQL queries based on the functional requirements expressed in natural language. This includes the implementation and validation of the queries generated using the proposed data model (Table 3).

The proposed scenario involved retrieving information on payments made by students to a school, considering only those with status of “Validated” or “In process.

Figure 15. *Results obtained from the prompt.*

Source. *Own elaboration (2026).*

The formulated prompt (Table 3) enabled the model to generate a properly structured SQL query, that met the established requirements, respecting the relationship of the tables by implementing JOINS and complying with the specified requirements. Figure 15 presents the code fragment generated by the artifact.

The model accurately identified the associations the data model entities and applied filtering criteria to retrieve only transactions corresponding to the specific payment types. Additionally, despite not being explicitly requested, the model concatenated the first and last name fields to construct the student's full name, thereby optimizing the query (Figure 16).

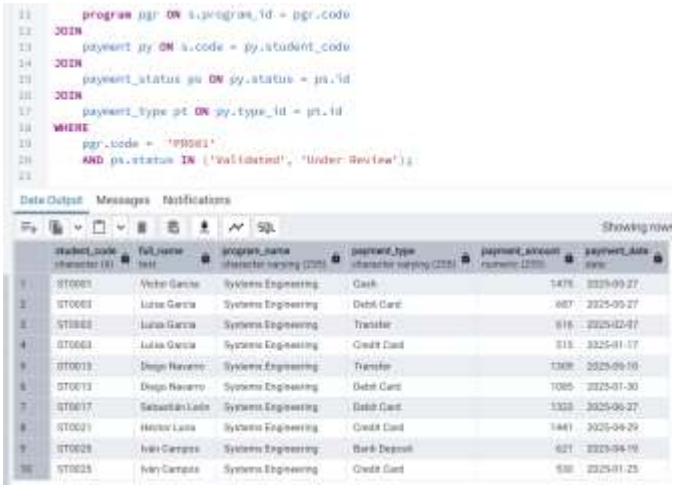


Figure 16. *Implementation of results in PostgreSQL Database.*

Source. *Own elaboration (2026).*

In terms of syntactic accuracy, logical coherence and clarity of data output, the result is considered satisfactory, demonstrating how a well-structured instruction can fully leverage the capabilities of the AI model in specialized data querying tasks.

5.2.2. Results of concept proof 2.

The second proof of concept focuses on evaluating ChatGPT's ability to generate functional backend code, using the Spring Boot framework, adhering to its conventional file structure. The scenario involved developing a module for student registration, which included uploading of a profile image. The required functionality included the implementation of a REST endpoint capable of receiving both the student’s data and an image file, storing the information in a database and saving the file in a local folder, at a specified path. The clarity of the prompt (Figure 17), designed following best practices, was the key to obtaining an accurate and fully functional response.

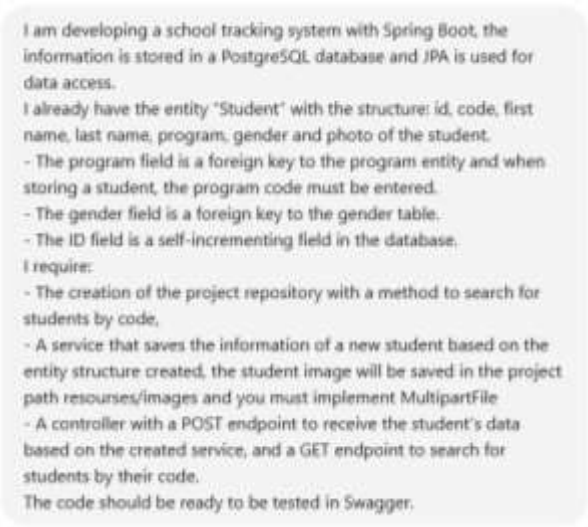


Figure 17. *Prompt generated for code phase.*

Source. *Own elaboration (2026).*

The generated prompt provided us with the components to generate the Repository, the Service, the Controller, and how to implement Swagger into our project as requested, in a sectioned manner. The codes can be seen in Figures 18 to 21. The generated structure was correct, and the AI understood the structure of the relationships between the tables as provided, so its results were generated with minimal errors. Similarly, the model shows how to modify the pom.xml file of our SpringBoot project to include the necessary dependency to interact with Swagger.

Figure 18. *Student Repository archive generated by ChatGPT.*

Source. *Own elaboration (2026)*

Figure 19. *Student Service archive generated by ChatGPT.*

Source. *Own elaboration (2026).*

Figure 20. *Student Controller generated by ChatGPT.*

Source. *Own elaboration (2026).*

Figure 21. *Swagger Implementation.*

Source. *Own elaboration (2026).*

The request specifies the intention to perform tests using Swagger. For this reason, the model demonstrates how to modify the pom.xml file to include the necessary dependency for interacting with Swagger.

Although the generated code was generally functional (Figure 22), several important issues were identified during the validation process. For example, the model changed the data type of

the gender entity from into long in the structure to save a student, which did not match the original structure of the entity, causing a mapping error. This type of automatic modification is evidence that, although the model can generate robust structures, it is necessary to carefully review the inferences made.

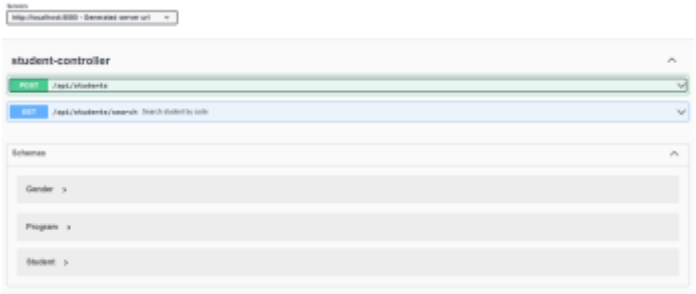


Figure 22. *Backend testing in Swagger.*

Source. *Own elaboration (2026).*

This proof of concept confirms that ChatGPT is a valuable tool for accelerating the development of common backend functionalities, particularly in controlled environments or during the prototyping phase. However, it is always recommended to thoroughly review the generated code, as potential issues such as data typing, variable names, or error handling evidence the need for the developer to maintain an active role during the integration of the generated code.

Results of concept proof 3.

The third proof of concept aimed to assess the effectiveness of ChatGPT in generating accurate and functional instructions to enable the deployment of a backend application developed with Spring Boot on an Amazon EC2 server running Amazon Linux 2023. The objective was to verify whether the model could assist in configuring a production environment from scratch covering tasks such as installing dependencies, configuring services, binding a custom domain, and exposing the system to the network.

The prompt provided (Figure 23) included essential details such as the operating system, the need to use the Spring Boot embedded server (no external container such as Tomcat), and the need to point the custom domain to the server.

Figure 23. *Prompt generated deployment phase.*

Source. *Own elaboration (2026).*

The response generated by the prompt was accurate and followed a clear step-by-step procedure, using updated commands along with security recommendations and best practices independent of the requested points. Part of the generated instructions and results can be seen in Figures 24 and 25.

The code and commands were successfully tested, enabling the replication of the environment on a real server without critical errors, in the GitHub repository https://github.com/VaniaMendez/ChatGPTPromptModel you can find the file with the complete results obtained with the prompt and the demo on AWS.

Figure 24. *Steps for configuring the domain in AWS.*

Source. *Own elaboration (2026).*

(a)

(b)

Figure 25. *(a) Steps for configuring the virtual machine; (b) Virtual machine configuration.*

Source. *Own elaboration (2026).*

To verify that our backend was deployed correctly, when entering the domain from a web browser, it should display the Swagger testing panel, as shown in Figure 26.

Figure 26. *Application deployed and tested in Swagger.*

Source. *Own elaboration (2026).*

In conclusion, this proof of concept demonstrated that ChatGPT can serve as a useful knowledge base for application configuration and deployment tasks, offering clear step-by-step guidance that can act as a starting point for developers with intermediate experience. Nevertheless, it is recommended that these instructions be complemented with official documentation, security practices and testing in staging environments before final deployment.

CONCLUSIONS

This work demonstrates the rapid advancement of language models, such as ChatGPT, in emerging roles within software development tasks, both at the academic level and in professional practice.

Data analysis indicated that approximately 81% of surveyed software developers used the tool in critical phases including coding, logical design, database queries, and technical documentation. ChatGPT is the most widely adopted AI in the current software development landscape. However, 60% of respondents expressed concerns about potential overreliance on AI, and more than 50% highlighted the need for a regulatory framework to accompany the integration of these tools into the software development life cycle, thereby reflecting a collective awareness of their ethical and professional impact.

The graphical analysis of the study variables (Table 1) revealed that the majority of users were in the 18-23 age group, suggesting a greater openness among younger individuals to adopt these technologies.

Based on these findings, a methodological artifact was developed to guide and facilitate the application of language models throughout the different phases of the software development life cycle. In organizational contexts, this type of resource is often referred to as a knowledge base: it documents and standardizes processes, practices, and lessons learned so that different team members can reuse them. Its use enables the capitalization of tacit knowledge and accelerates procedures, thereby reducing the learning curve for new collaborators.

The artifact was subsequently tested under three real-world scenarios to demonstrate its practical effectiveness:

The first proof of concept focused on generating a multi-table SQL query. ChatGPT produced an accurate and actionable response, proving that it can assist with database tasks, provided that the prompt is well structured and detailed. It allows complex data to be extracted easily, without the need for extensive documentation or manual coding.

The second proof of concept involved generating a backend module for a web application developed with Spring Boot, supporting student registration and image upload. Despite the correct functionality, an error was detected in the data type of the sex field, which changed from int to long. This highlights the persistent margin of error and confirms that developers must carefully review AI-generated code. This case underscores the importance of being specific and clear regarding expected attributes, relationships between tables or variables, and desired behaviors in order to obtain a functional code.

The third proof of concept involved requesting a detailed guide for configuring a custom domain, creating an EC2 instance in Amazon Linux 2023, installing Java 21 and PostgreSQL 16, configure NGINX as a reverse proxy, and enable secure access. It was demonstrated that, if the prompt is not sufficiently specific, ChatGPT may provide vague or unhelpful responses. However, by using the methodological artifact as a reference, it was possible to obtain a detailed and accurate sequence of steps that facilitated the full setup—including the use of WinSCP to upload .jar file and access the Swagger interface. This case highlights that, for infrastructure-related topics, prompt precision is even more critical.

The implementation of this artifact in business environments represents a strategic opportunity to standardize the use of language models in the software development life-cycle. Its structural approach enables development teams to integrate more efficient, systematic, and collaborative processes when interacting with AI tools, reducing common errors in requirement formulation and improving the traceability of technical decisions. By integrating this artifact into DevOps environments, technical backlogs, documentation processes, or code reviews, companies can not only accelerate productivity but also strengthen the quality and consistency of the generated software, ensuring that the use of artificial intelligence remains transparent, justified, and aligned with their technological objectives.

However, it is important to emphasize that these tools are not recommended for testing tasks, as they present limitations in understanding complex logical contexts, identifying edge cases, or generating reliable automated tests. Therefore, the validation and quality assurance phases should remain the responsibility of developers.

Final Recommendations:

- Use clear prompts that include technical context and well-defined objectives.
- Always validate the results delivered by the model, even for simple tasks.
- AI is integrated in phases such as design, coding, and documentation, but not in testing.
- We leveraged the benefits of an internal knowledge base built from effective interactions with AI models.
- Provide training for development teams on the critical and responsible use of generative tools.

The methodological artifact presented in this work is the first step toward the controlled and effective integration of these models in real-world software development tasks, fostering collaboration between human expertise and intelligent systems within the development workflow.

Finally, it is recommended that the use of ChatGPT and similar models remain a support tool, not a replacement for professional judgment. The most effective way to leverage this technology is to craft detailed, structured, and contextualized prompts, as proposed in the artifact. It is essential to explicitly define what is being done, what is required, what attributes the solution must have, what the technological environment is, and what behavior is expected. These practices not only optimize outcomes but also enable a more ethical, efficient, and professional use of artificial intelligence in the field of software development.

Acknowledgements

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All authors will be updated at each stage of manuscript processing, including submission, revision, and revision reminder, via emails from our system or the assigned Assistant Editor.

Data Availability Statement: The data that support the findings of this study are openly available in Data from a study of AI tools currently used by professional at https://zenodo.org/records/, reference number 16975651.

Conflicts of Interest: The authors declare no conflict of interest. **Institutional Review Board Statement:** This study, was conducted in strict compliance with ethical principles and applicable legal regulations regarding personal data protection and human participation in research. The "NO APPROVAL REQUIRED" by an ethics committee or institutional review board is justified given the scope and specific nature of the research, which did not involve the collection of sensitive data or the exposure of participants to physical, psychological, or social risks. In accordance with the Federal Law on Protection of Personal Data Held by Private Parties (LFPDPPP), the collection of personal data is lawful provided that the principles of legality, consent, information, quality, purpose, loyalty, proportionality, and responsibility are complied with. The research was designed and implemented under these precepts, guaranteeing the privacy and protection of respondents' data. Informed Consent Statement: Participants in the study were clearly informed in advance about the purpose of the processing of the information (exclusive use for academic and scientific purposes) through an introductory text on the digital survey platform. Participation was voluntary, and the act of responding to the questionnaire was interpreted as express consent on the part of the respondents, who, by completing it, confirmed their understanding and agreement with the terms presented. No images, recordings, or sensitive data that could compromise the privacy of participants were collected.

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