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How does Artificial Intelligence contribute to the performance improvement of software development companies?

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Patras, Greece, March 2025

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“To my family”

Abstract

Today's modern software companies face numerous challenges, including the rapid acceleration of hardware capabilities and the growing demands of consumers who rely heavily on software applications. These challenges compel software development companies to reassess their operational processes and utilize all necessary tools to enhance productivity and achieve improved performance.

At the same time, artificial intelligence has made giant steps toward advancement, and professionals are using it in almost all business domains as it can be applied in many industries. The latest AI models can be trained dynamically, perform image processing, and produce outputs that can emulate human language. AI has begun to be used in nearly all domains of the software industry, including software development, quality assurance, and project management.

This study tries to address the following topics:

- Identify the significant challenges that software development companies face.
- Explore how AI can be used in the software development lifecycle and its contribution to the performance of software development companies.
- Assess the impact of AI on software development, quality assurance, project management, and human resource processes.
- Propose ways for software development companies to easily adopt the use of AI.

The method used for this research involved distributing a questionnaire to software industry professionals. The study concluded that although professionals often utilize AI, they perceive benefits only in certain aspects, while AI usage still faces limitations, including a lack of consistency and high costs. As software development companies are expected to invest in AI adoption over the next two years, it is of high importance to invest in training and workshops, as well as to have the required managerial support, to proceed with the necessary organizational changes.

Keywords

Artificial Intelligence, Software Development, Organizational Performance.

Περίληψη

Οι σύγχρονες εταιρείες λογισμικού αντιμετωπίζουν πολλές προκλήσεις, όπως η επιτάχυνση των δυνατοτήτων του hardware και η αυξανόμενες απαιτήσεις των καταναλωτών, οι οποίοι βασίζονται όλο και περισσότερο σε εφαρμογές λογισμικού. Αυτές οι προκλήσεις αναγκάζουν τις εταιρείες λογισμικού να βελτιστοποιήσουν τις διαδικασίες και να χρησιμοποιήσουν τα απαραίτητα εργαλεία για να βελτιώσουν την παραγωγικότητά τους. Ταυτόχρονα, η Τεχνητή Νοημοσύνη (TN) έχει σημειώσει τεράστια πρόοδο και χρησιμοποιείται από επαγγελματίες σχεδόν σε όλους τους τομείς. Τα πρόσφατα μοντέλα TN όχι μόνο μπορούν να εκπαιδεύονται δυναμικά, αλλά και να εκτελούν επεξεργασία εικόνας και να παράγουν αποτελέσματα που προσομοιώνουν την ανθρώπινη γλώσσα. Η TN έχει αρχίσει να χρησιμοποιείται σχεδόν σε όλους τους τομείς των εταιριών πληροφορικής, όπως η ανάπτυξη λογισμικού, η διασφάλιση ποιότητας και η διαχείριση έργων.

Η παρούσα μελέτη προσπαθεί να θίξει στα ακόλουθα θέματα:

- Να προσδιορίσει τις κύριες προκλήσεις που αντιμετωπίζουν οι εταιρείες μηχανικής λογισμικού.
- Να διερευνήσει πώς μπορεί να χρησιμοποιηθεί η TN στον κύκλο ανάπτυξης λογισμικού καθώς και την συνεισφορά της στην απόδοση των εταιριών .
- Να αξιολογήσει τον αντίκτυπο της TN στην ανάπτυξη λογισμικού, τη διασφάλιση ποιότητας, τη διαχείριση έργων και τις διαδικασίες διαχείρισης ανθρώπινου δυναμικού.
- Να προτείνει τρόπους με τους οποίους οι εταιρείες μηχανικής λογισμικού θα μπορούσαν να υιοθετήσουν ευκολότερα τη χρήση της TN.

Η μέθοδος που χρησιμοποιήθηκε για την έρευνα είναι ένα ερωτηματολόγιο που διανεμήθηκε σε επαγγελματίες που εργάζονται στις εταιρίες λογισμικού. Η μελέτη κατέληξε στο συμπέρασμα ότι, παρόλο που οι επαγγελματίες χρησιμοποιούν συχνά την TN, βλέπουν οφέλη μόνο σε ορισμένους τομείς, ενώ η χρήση της TN εξακολουθεί να αντιμετωπίζει περιορισμούς, όπως η έλλειψη συνέπειας και το υψηλό κόστος. Καθώς οι εταιρείες μηχανικής λογισμικού αναμένεται να επενδύσουν στην υιοθέτηση της TN τα επόμενα χρόνια, είναι σημαντικό να επενδύσουν σε εκπαίδευση, εργαστήρια και την απαραίτητη διοικητική υποστήριξη, ώστε να προχωρήσουν στις αναγκαίες οργανωτικές αλλαγές.

Λέξεις – Κλειδιά

Τεχνητή νοημοσύνη, ανάπτυξη λογισμικού, οργανωτική απόδοση.

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List of Abbreviations and Acronyms

AI	Artificial Intelligence
ICT	Information Communication Technology
IT	Information Technology
SDLC	Software Development Life Cycle
NLP	Natural Language Processing
ML	Machine Learning
LLM	Large Language Model
LM	Language Model
PMO	Program Management Office
R&D	Research and Development
GUI	Graphical user interface
ROI	Return on Investment
QA	Quality Assurance
PM	Project Management
HR	Human Resource

1. Introduction

Over the last few years, Artificial Intelligence (AI) and its impact on various industries have been the subject of research studies and a central topic of discussion among professionals. The use of AI in daily work has become increasingly frequent, driving numerous changes across industries, and software development companies are no exception as they strive to optimize their organizational performance.

1.1 Problem Statement

In recent years, the growth of the software development industry has been significant, driven by the need to digitalize services, the technological revolution, and the adoption of automation software across various industries. However, this growth has not been without challenges: the demand for rapid delivery of quality software, rising costs, and increasing customer expectations have heightened complexities. Software companies must adapt to maintain operational efficiency, productivity, and competitiveness. This evolving landscape forces development companies to try to integrate innovative tools in order to enhance their performance.

The benefits of AI in task automation, adaptability to changing requirements, and the ability to generate proposals seem to effectively address the challenges of this fast-paced environment. AI has already demonstrated its potential in natural language processing (NLP), machine learning (ML), and predictive analytics, all of which are relevant to software development processes. However, This MBA dissertation will try to address the following question: How does AI contribute to the performance improvement of software development companies?

1.2 Research Objectives

This MBA dissertation aims to investigate the contribution of AI to the performance improvement of software development companies and will try to answer the following questions:

1. Identify and point out the significant challenges that software development companies face in maintaining their performance.

2. Examine how AI can be applied across the various stages of the Software Development Lifecycle (SDLC).
3. Evaluate the impact of AI on development, testing, quality assurance, project management practices, and human resources (HR) processes.
4. Recommend how software development companies can effectively integrate AI technologies.

A questionnaire will be distributed to software development professionals to gather and analyze their opinions, as they are the primary beneficiaries of the information. This will help us understand how AI addresses modern industry challenges and how companies can effectively adopt it.

1.3 Importance of operational efficiency in software companies

Operational efficiency and performance are defined as maximizing output while minimizing input without compromising quality (Rahman, 2024). For software development companies, it is not just about cutting costs or boosting productivity; it also involves integrating technology, managing processes, and effectively utilizing human resources (Rahman, 2024). Complex workflows should be managed alongside cross-functional team coordination to ensure seamless communication across different development stages and achieve on-time project delivery and high-level services.

Despite implementing agile methodologies and advanced project management tools, challenges such as repetitive tasks, debugging issues, and evolving requirements often derail projects, resulting in increased costs, diminished quality, and damage to the company's reputation. At the same time, operational inefficiencies compromise the delivery of high-quality services.

AI offers an opportunity to address these challenges by automating repetitive tasks, providing data analysis summaries for informed decision-making, and facilitating risk prediction.

1.4 Methodology and Approach

This research approaches the subject in the following ways: It critically reviews the literature and related studies to identify the significant problems faced by software development companies, the key AI technologies, and how their application helps performance

improvement. Furthermore, surveys will be distributed to software development professionals to gather data and analyze the extent to which professionals incorporate AI into their daily work. The quantitative research will be based on the guidelines outlined in the APA Dictionary of Psychology (2018), utilizing a numerical system to measure variables, analyzing these measurements using various statistical models, and reporting relationships and associations among the studied variables. The following diagram depicts the steps that will be followed in the scope of this dissertation thesis.



Figure 1: Research steps.

1.5 Brief chapter description

This Study consists of 6 chapters:

- Chapter 1: Introduction. It presents the problem under investigation, the study's objectives, the necessity for the research subject, and the investigation approach.
- Chapter 2: Organizational Performance. A literature review and related work on organizational performance within software development companies. This chapter introduces the fundamental concepts of the research topic, including the definition of performance and its measurement methods. It also examines its connection to the operations of software companies and the challenges faced by modern organizations.
- Chapter 3: Artificial intelligence. This chapter presents the concept of artificial intelligence, its evolution, and its significant applications, as well as the impact of AI on performance factors.
- Chapter 4: Methodology and research approach. This chapter presents the methodology, research approach, and questions that professionals diffused.
- Chapter 5: Findings. This chapter presents the statistical analysis of the results, along with an examination of the variables.
- Chapter 6: Discussion of the results. This chapter summarizes the key findings and proposes strategies for software development companies to effectively adopt AI.
- Chapter 7: Conclusion. This chapter presents the conclusions drawn from the results, as well as recommendations on how AI can be best adopted.

2. Organizational Performance

This chapter discusses performance in software development companies, examining how productivity influences it, how it can be measured and monitored, and what other factors contribute to its formulation. It also addresses the challenges modern development companies face and outlines the primary software development methodologies used for developing new software projects.

2.1 Performance in Software Development Companies

2.1.1 Organizational Performance and Productivity

Organizational performance is a crucial concept in the business world. It is a broad term that covers not only productivity but also all economic and operational aspects (Tangen, 2005). It is the ability to compete and meet customer expectations by delivering high-quality services and products. Quality plays a vital and integral role in achieving organizational performance.

Organizational performance concerns not only new development but also operations. Typically, after a new product or service is developed, it is passed on to operations.

Operational performance can be attained through five objectives, as illustrated in the figure below (Slack et al., 2010):

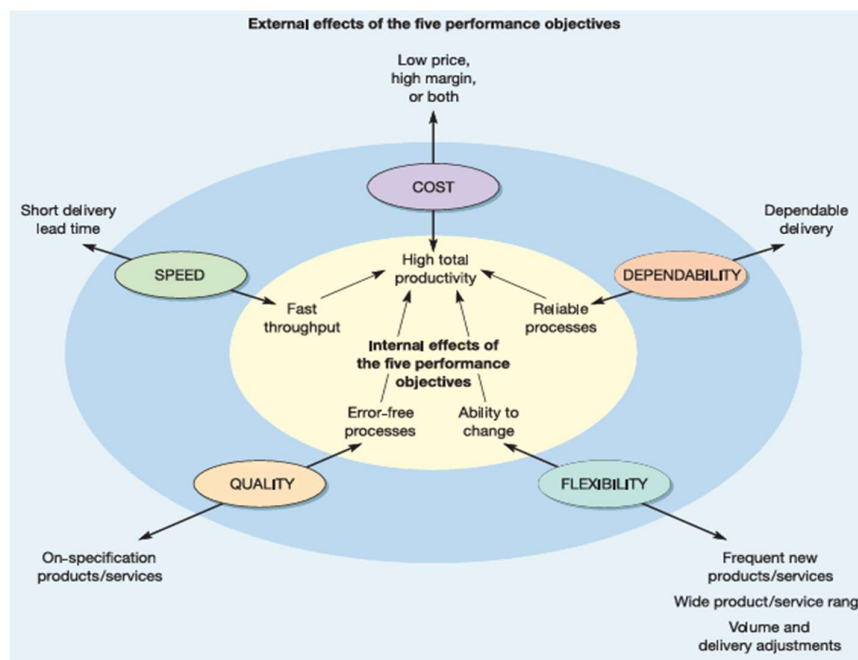


Figure 2: Performance objectives (source: Slack et al., (2010))

- Speed is the ability to deliver quickly once an order is received. Speed is achieved with fast throughput and short delivery lead time.
- Quality is the ability to meet customers' expectations and provide flawless products and services. Quality is achieved through error-free processes and products or services delivered according to specifications.
- Cost refers to the ability to be cost-effective, have efficient resource allocations, and be able to produce at low prices.
- Flexibility is reacting to changing demands and accommodating last-minute changes. It is achieved by modifying, adapting, and frequently delivering various products.
- Dependability is the ability to deliver dependent services on their scheduled time so that operations are unaffected. It is achieved through practical, reliable services and effective delivery planning of dependent products and services.

According to Slack et al. (2010), high-performance operations:

- Do not waste time or effort repeating the same things. They use the same components to improve effectiveness.
- Provide a flawless service. Services run as expected, according to specifications.
- Reduce administrative overhead. Many tasks are executed automatically.
- Deliver precisely as planned. The timely delivery of services is essential for achieving performance.
- Maintain flexibility and adaptability without affecting concurrent operations.
- Are cost-effective, leading to higher profits.

Although the above performance goals mainly concern operations, the development of products and projects should also adhere to these principles for successful completion.

Productivity constitutes a prominent part of the organizational performance concept. Hill (1993) states that "Productivity is defined as the ratio of what is produced to what is required to produce it. Productivity measures the relationship between output such as goods and services produced, and inputs that include labor, capital, material, and other resources". Performance excellence presumes efficient and effective productivity for on-time task completion.

Productivity affects all project or product activities as it influences costs, schedules, and quality. Low productivity rates lead to increased costs, missed milestones, and outputs of

inadequate quality. Grunberg (2004) states that productivity is the company's production ability, and the following metrics can measure it:

- Total Factor Productivity (TFP): TFP measures the value added by the inputs (capital and labor) used. It is a long-term economic metric as it encompasses broader financial considerations.
- Output per hour worked: This metric is a partial measure as it reflects labor productivity. It indicates the amount of output produced by the labor force.
- ROI: This metric is a financial measure that shows whether the initial investment was sufficiently efficient.

Ghobadian & Husband (1990) classify the definition of productivity into three aspects:

- Technological: ratios of output to inputs. Measures how efficient the delivery of outputs is compared to the used inputs.
- Engineering: Difference between the theoretical and the actual output of a process. Measures how efficient the delivery of outputs is when compared to the predicted one.
- Economical: How efficiently the resource is allocated. The correct utilization of resources is crucial for optimizing productivity.

Sudhakar et al. (2012) underline the importance of measuring productivity and performance. Measuring productivity helps identify underutilized resources because higher productivity leads to lower costs.

2.1.2 Performance in Software Development Companies

For software development companies, performance plays an essential role. According to Symons (2010), in the software industry, the following performance indications can be used to measure how the delivery of products and services is performed:

- Productivity: the ratio of the size of software delivered to project effort or size of the application developed to the labor consumed during development (Sudhakar et al., 2012).
- Speed of delivery: the ratio of the size of software delivered to project elapsed time.
- Function Points delivered: This is an alternative method for measuring the size of software delivered, based on IFPUG or COSMIC methods. The COMSIC Function Points method seems to produce more precise results.

- Quality of delivered software: the ratio of defects recorded post-delivery to software size. A bug-free software, developed using efficient quality procedures, contributes to organizational performance.
- Budget delivery is the ratio of the actual cost to the estimated cost. It is crucial for software companies' financial viability to not only cover their costs but also obtain a margin after the project is completed.
- Delivery to time: the ratio of actual elapsed time to estimated time. Completing projects on time is crucial for meeting customer expectations and managing costs effectively.

The factors influencing the aforementioned indicators, including the efficient and effective execution of the software development life cycle, the accurate implementation of project management practices, and the practical allocation and utilization of resources, can significantly impact the organizational performance of software development firms. This emphasizes the importance of using all necessary tools to ensure the successful implementation of the software process improvements.

Concerning the project management aspect of performance, Aubry (2011) found that although research on organizational performance in project management does not yield satisfactory results, project management offices (PMOs) can still influence organizational performance.

Syalevi et al. (2024) also highlight that an effective program management office (PMO) that supports project managers in successfully executing projects contributes to strong organizational performance by providing them with practical tools for efficiently executing their activities.

Ollows (2012), in his dissertation, "Impact of project management practices on organizational performance of small and medium-sized enterprises: a case of Letan Limited," found that project management practices play an important role in achieving better organizational performance, with cost and scope management playing the most important role.

According to Anwar (2021), human resource management (HRM) encompasses a range of tasks, including HR planning, managing human resources, strategic recruitment, employee training, compensation management for growth and efficiency, employee relations, healthcare, employee satisfaction, and the provision of employee services. Companies

depend significantly on their employees' skills to provide quality services in their pursuit of a competitive advantage. In his article, he points out the primary HRM practices that directly affect organizational performance:

- Incentives. This includes motivating and retaining employees, compensating them fairly, rewarding them effectively, and implementing clear commitment policies.
- Employee training. This includes the quality and customer focus policy. Employees should be able to perform their work while maintaining a focus on client satisfaction.
- Selective hiring. This includes the policy of finding and hiring the best talent available.
- Job security. Professionals, when they feel secure and valued, demonstrate increased productivity.
- Self-managed teams & Decentralization.

Preeti (2023) found that effective recruitment and selection processes have a positive influence on organizational performance. The same applies to the other HR processes, such as training, development, and performance appraisals. The most crucial factor is the correct and accurate selection of talents to add value to the delivery of products and projects.

Sudhakar et al. (2012) state that several factors influence the productivity and performance of software companies, including software development and testing tools, document management systems, and configuration management systems. Moreover, characteristics of the product and process, as well as team size, play a role in productivity. The experience and effectiveness of the project manager are equally significant. Lastly, productivity may vary across different business sectors and among various companies.

2.1.3 Performance Metrics in the Software Industry

Several measures have been used over the years to qualify and measure performance in the software industry. These measures should not be used independently but in combination with other measures, taking into account the circumstances and the type of software solution being developed.

According to Eisty et al. (2018), the primary performance metrics are:

- Deployment Frequency: It measures how many deployments the teams can deliver in a given period.

- Lead time to change: It measures the time it takes to go from code committed to code running in production.
- Time to restore service: This measures the time it takes to restore service after the incident occurs.
- Change failure rate: It measures the percentage of changes to the service application that result in degraded service.
- Backlog Management Index: It measures the effectiveness of a team's backlog management process.
- Code coverage: % of new code covered by integration tests.

According to Kan (2003) and Banker et al. (1991), the primary quality metrics are:

- Mean Time to Failure: It calculates the average time a product or system functions before its first failure under normal conditions.
- Defect Density: It calculates the number of defects detected per line of code or module.
- Defect Arrival: It calculates the amount of additional testing required before the system can be released.
- Mean Time to Reshipment: It measures the time it takes to deliver a fix for a known issue to the customer.

Other notable productivity metrics that also affect performance are:

- Productivity = Number of Function Points / Effort in Man months (Blackburn et al., 2002). It calculates the size of the software delivered at a given time.
- Productive Ratio= % of Direct Development time / % of Idle time. It considers the complexity, changes in requirements, and development time (Nogueira et al., 2000).
- Analysis/Design Activity Output measure =Function Points/ Total Labor hours. It measures the time it takes to analyze and design the solution (Banker et al., 1991).
- Coding/Testing Activity = Source Lines of Code/Total Labor Hours. This measures the time the team took to develop and test the solution (Banker et al., 1991).

Eden & Mens (2006) suggested utilizing evolution cost metrics to evaluate flexibility when executing specific evolution steps. Flexibility relates to change, and there are always limits to the number of adaptations a product can undergo.

Crouzet & Kanoun (2012) mention that the dependability performance objective encompasses several attributes, including availability, reliability, safety, confidentiality,

integrity, and maintainability. Reliability measures the continuous delivery of correct service and the time to failure; availability measures the delivery of uninterrupted service; maintainability measures the time to restore service; and safety measures the absence of catastrophic events.

Finally, cost performance is measured by the ROI of the development.

2.1.4 Problems of Modern Software Development Companies

Software Development companies face many challenges nowadays, as multiple factors affect their performance. Fitzgerald (2018) states that modern software companies face many challenges caused by push and pull factors. Push factors include significant advancements in hardware, such as quantum computing, IoT (Internet of Things), and Systems of Systems, which offer immense potential for data processing, enhanced general processing capabilities, and new horizons. On the other hand, pull factors consist of consumers who rely heavily on software applications, expect more complex and extended solutions, and the industry heavily dependent on software solutions. To meet this necessity, software development companies must achieve high performance.

Furthermore, software development companies are facing the rising cost of skilled software developers (Udoidio et al., 2024), which presents a significant challenge for the software industry. Meanwhile, their expertise is crucial for delivering innovative solutions. Simultaneously, cloud technologies are becoming more widespread, opening up new opportunities and compelling companies to undertake not only cloud migrations but also develop new skills to offer competitive services and stay ahead of the latest technological trends.

This new reality comes on top of classic software project problems, according to Wang (2023), Mohan & Greer (2018), Batarseh et al. (2020), and Shehab et al. (2020):

- Customers' requirements are not always translated correctly into product specifications. Due to tight deadlines, the time available to analyze and process customer expectations is usually minimal. In addition, even though most companies nowadays implement hybrid or Agile methodologies, the fast pace of technological advancements and continuously changing user demands make accommodating changes very demanding. Manually converting informal requirements to formal specifications is error-prone and time-consuming.

- Budget overruns are common in the software industry as tasks are not estimated sufficiently and correctly, and the requirements are poorly defined. At the same time, project managers, to keep clients happy, tend to accept last-minute changes in requirements, thus causing many delays without considering the additional costs that may be incurred. Additionally, risk identification and mitigation strategies are often poorly designed or not effectively implemented.
- Schedule, scope, and budget constraints often lead to inadequate testing. Thorough testing typically demands significant time and resources, which most companies struggle to allocate. Creating meaningful and comprehensive test cases is a challenging and time-consuming task. Consequently, projects encounter numerous quality issues, recurring mistakes, and reworks.
- Software changes are often poorly documented, complicating verifications and creating obstacles during maintenance. A significant amount of effort is spent on identifying the specifications and determining how the software needs to function before commencing the actual development work.
- Miscommunication between stakeholders, including development, testing teams, and users, can lead to delays and misaligned expectations.
- As the complexity grows, traditional methods of analyzing and managing requirements fail to keep up.
- Not much time and budget are spent on the design phase, but it has a very high impact during the implementation phase.
- During testing, the budget is usually insufficient to perform regression testing every time the software changes because testing already consumes around 50% of the project costs, and at the same time, automating testing often fails to identify errors related to specific use cases. Furthermore, testing requires skilled testers, which increases the cost and significantly increases time investments (Khan et al., 2024).

During the execution of the development and testing phase, the following common issues are observed (Khaliq et al., 2022):

- Writing efficient and bug-free code is time intensive. Much time is spent on software reviews, comments, and changes before delivering the code to higher environments to be verified.

- Locating bugs is also time-consuming, especially in large codebases. If the code is poorly written, the time to identify the place of the bugs, perform changes, and regression testing is significant.
- Refactoring the code to reduce technical debt is error-prone and often leads to regression issues. Although the reduction of the technical debt is essential, if it is not performed without the proper analysis, it can create many issues.

Project managers also face the following issues (Mohammad & Chirchir, 2024; Odeh, 2023):

- They often deliver inaccurate project plans due to incomplete data, as they rely on historical data for planning activities such as effort estimation, resource allocation, and predictions.
- They often see their plans derailed due to schedule delays, resource availabilities, communication breakdowns, or logistical complications. Effective and efficient project management is the backbone of correct project execution.
- They also face issues regarding manual and repetitive tasks, constant tracking and changes, prioritization of issues and tasks, and Inefficient internal systems (Butt, 2018).

Finally, Patil et al. (2011), in their article, conclude that modern software companies face the following Human Resource process challenges:

- Recruitment planning. Coordination between the company's needs and available profiles is of utmost importance.
- Performance management. Opportunities for performance enhancements should always align with the company's culture.
- Training and development. Employees should be able to perform their tasks fortified with appropriate training.
- Compensation management. The IT industry is one of the most competitive industries in terms of salaries. As a result, IT companies should be able to offer competitive compensation packages.
- HRM as a whole. IT companies face a high attrition rate, and considerable effort should be invested in minimizing this rate.

2.2 Software Development Life Cycle (SDLC) and Methodologies

2.2.1 Software Development Life Cycle

To understand how AI can improve the performance of software development companies and in which phases of Software development AI can be leveraged, it is essential to understand the SDLC stages and analyze the software development methods. The figure below presents the typical phases of the SDLC (Mohammad, 2023):

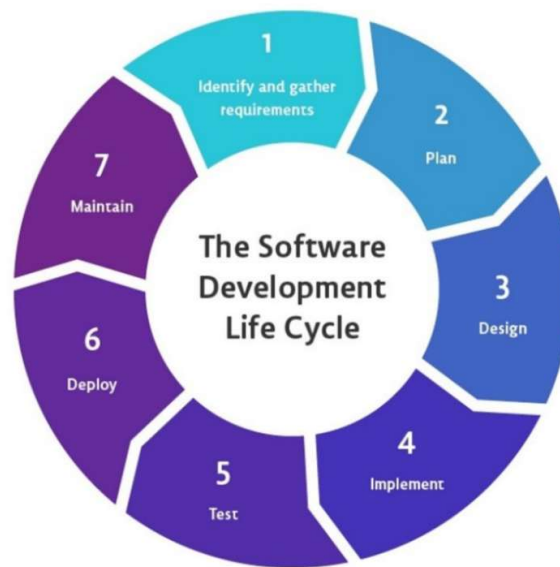


Figure 3: SDLC (source: www.cloudemployee.io)

- Identify and gather requirements phase: During this phase, scope, objectives, and requirements are defined. Customers' expectations are clearly defined and communicated so that everyone is aligned with the project's expected outcome. This phase will also serve as the foundation for project planning.
- Planning phase: During this phase, plans for scheduling, cost, and resources are drafted. The identification of stakeholders and, of course, the establishment of communication channels are also part of this phase. Project managers and stakeholders are involved in defining plans, allocating resources, setting timelines, and establishing milestones and budgets.
- Design phase: During this phase, the software's architectural solution, technical specifications, user interface designs, data models, and user experience designs are completed. The software development and testing teams will use these designs to deliver the projects.

- Implementation phase: During this phase, the actual development is performed according to the architectural solution. Unit testing is implemented to verify that the components are working as expected.
- Testing and Integration phase: During this phase, the different components are integrated. This stage then verifies the software solution's functionality, performance, and compatibility. Integration, system, and acceptance tests are usually performed during this stage, and any issues and defects are corrected.
- Deployment phase: During this phase, the software is deployed to staging and production environments. The deployment is usually performed automatically using the deployment pipelines. Before the deployments, the machines are usually configured appropriately.
- Maintenance and support: During this phase, the application is monitored and maintained. All the issues that users report are addressed, along with updates, improvements, or necessary patches.

2.2.2 Software Development Models

There are various methodologies used in software development (Mohammad, 2023). Project managers and delivery leads apply these methodologies to guide and lead development and testing teams. The major ones are:

- Waterfall model: This model provides a structured and linear approach to the software development life cycle (SDLC) methodology. It divides the software development process into distinct, sequential phases. It assumes that the requirements are entirely and precisely defined. Comprehensive documentation is also a prerequisite for this model, as everything needs to be thoroughly documented. Customers are primarily involved during the requirements definition phase. Testing is typically carried out at the end of the development phase. The waterfall model emphasizes the implementation of robust and structured project management processes, including planning and control, as well as the effective utilization of project management tools.
- Agile Model: It combines iterative (repetitive development cycles resulting in partial product versions) and incremental approaches (dividing a project into small, controllable segments). Agile projects are divided into short, deliverable-based

units, known as sprints. Agile methodology is based on the close collaboration between development and testing teams and customers and is suitable for projects with evolving or frequently changing requirements. It ensures flexibility, adaptability, and continuous delivery of the product and is considered to be customer-centric.

- Hybrid model: This model often combines Waterfall and Agile methodologies. It is mainly chosen when the requirements are well-defined, but the delivery needs to be made in increments.
- V model: This model is similar to the waterfall model in that the phases are linear. Its phase should be finished before the next phase starts. However, testing plays an essential role in this model. Testing procedures are developed very early in each phase before the implementation starts.

2.2.3 Quality Assurance Methodologies

It is also essential to understand what quality is in software companies and how it is achieved. First of all, it should be explained what software testing is: The definition of testing according to the ANSI/IEEE 1059 standard is the process of analyzing a software item to detect the differences between existing and required conditions (that is defects/errors/bugs) and to evaluate the features of the software item. Software testing involves verifying if the actual results of the software align with the expected outcomes based on its requirements and specifications. It ensures that the software is free from defects. The primary goal of software testing is to identify errors, faults, discrepancies, and missing functionalities that do not meet the specified requirements.

Software testing types are as follows:

- Manual testing: Testing the software manually without the use of any automated tools or techniques scripts.
- Automated testing: It is also known as “Test Automation”, which involves the tester writing scripts and using another software to test the software (Hourani et al., 2019).

Software testing life cycle phases take place throughout the software development life cycle (SDLC):

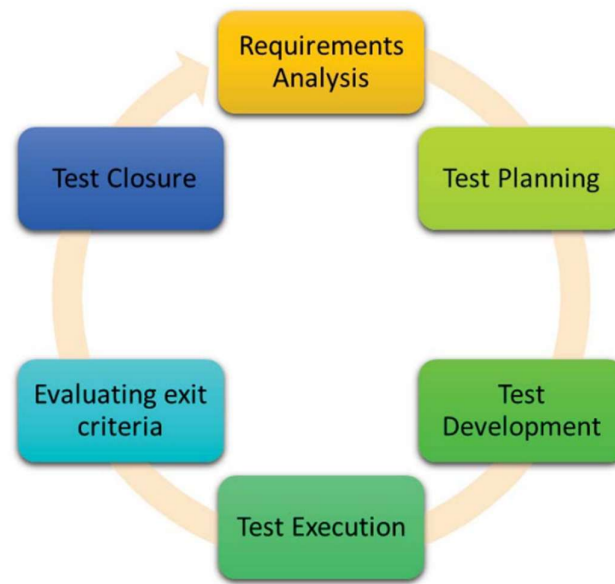


Figure 4: Testing Life Cycle Phases (Source: Hourani et al., (2019))

- **Requirements Analysis:** During this phase, the testing team analyses how the software is expected to work.
- **Test Planning:** This phase involves defining the necessary schedules, resources, and configurations.
- **Test Development:** During this phase, the test cases and scenarios are developed.
- **Test Execution:** During this phase, the test cases are executed to determine whether the product meets the requirements.
- **Evaluating Exit Criteria:** During this phase, the results are analyzed. Usually, there is a threshold under which the testing cycle is considered to have failed. Also, during this phase, the change management process is initiated.
- **Test Closure:** During this phase, the necessary documents, including test reports and recommended actions, are produced.

The testing procedure occurs at all levels: during the development, release, and acceptance phases.

2.3 Summary

This chapter presents the complex landscape of measuring and achieving optimal performance in software development companies. It also presents the pillars upon which performance depends, such as human resource practices, productivity, project management practices, and quality, and analyzes their importance in relation to overall performance. Essential performance indicators are presented, along with the various challenges that

modern businesses face, and a discussion of the fundamental methodologies that influence development processes is also included.

AI emerges as a solution for addressing the challenges mentioned above. It automates repetitive tasks, enhances data analysis for better decision-making, and anticipates potential issues before they arise. By utilizing machine learning algorithms, businesses can optimize resources, improve project planning, and increase the accuracy of effort estimates. Moreover, AI-powered tools can streamline testing processes, identify code defects, and assist in continuous integration and deployment. AI's ability to address common project management challenges makes it a valuable resource for modern software development companies seeking to achieve and maintain a competitive edge.

3. Artificial Intelligence

This chapter discusses the progress of AI, its capabilities, and its significant domains and applications, as highlighting the evolution of AI is essential to understanding its current state and potential. It also presents the existing work on the impact of AI on performance improvements. Finally, it discusses existing research on the impact of AI across various areas of software development that influence performance, including project management, software development, quality assurance, and human resources processes.

3.1 AI evolution and capabilities

3.1.1 AI Evolution

Artificial intelligence is not something new. The Dartmouth conference in 1956 is considered to be the birthplace of AI (Shehab et al., 2020). Since then, the evolution and development of AI have marked many milestones (Jaiwal et al., 2023; Glushkova, 2023, “Main stages of evolution of AI” (p. 8-9)):



Figure 5: Evolution of AI

- Rule-based AI (1950s -1960s): Predetermined logic is used to develop rule-based systems. These systems cannot learn but react when a specific scenario or condition is realized.
- Neural Networks (1980s): During this time, the systems' behavior evolved in response to incoming information. They no longer rely on fixed scenarios and represent the first generation of systems capable of learning over time.
- Machine Learning (1990s-2000s): These systems are now capable of learning from extensive datasets and predicting outcomes through algorithms such as decision trees (Bishop & Nasrabadi, 2006).
- Deep Learning and Modern AI (2010s—present). Deep learning represents an advancement in the field of Machine Learning, leveraging multi-layered Neural Networks. These networks possess the capability to extract complex features from unprocessed data and perform sophisticated tasks such as image processing and speech recognition.

3.1.2 Domains and Applications of AI

According to Jaiwal et al. (2023), Barenkamp et al. (2020), Aishwarya et al. (2022), and Bhavsar et al. (2019), the domains of AI can be classified into the following areas of domains:

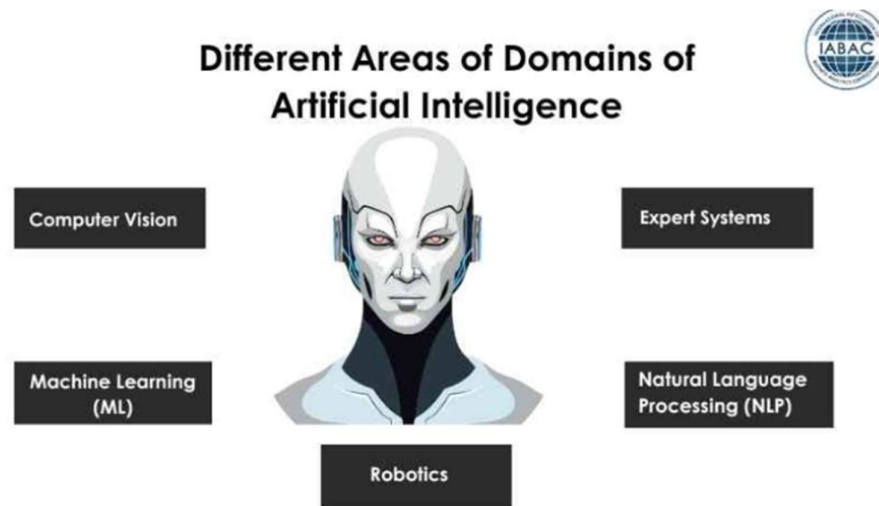


Figure 6: Domains and applications of AI (source: iabac.org)

Machine Learning (ML):

ML focuses on training models using large datasets and making decisions without explicit instructions on how to do so. It represents an evolution of Neural Networks, and its strength lies in refining results over time through learning. It can improve processes by accessing information independently, rather than relying on preset algorithms. Numerous online streaming services utilize machine learning (ML) to suggest relevant content to their users. Deep learning is another type of machine learning. Deep learning utilizes neural networks, a system of interconnected nodes that is modeled on the human brain.

Natural Language Processing (NLP):

NLP is heavily based on deep learning, combining machine learning (ML) and Neural Networks. It enables interaction between computers and humans, allowing for the understanding and generation of human language. Chatbot applications rely on NLP to provide services.

Expert Systems:

Expert systems mimic the human decision-making process using predefined rules and data sets. They are often used in financial markets to help analysts.

Robotics:

Robotics entails the development of intelligent machines designed to engage with their environment. Robotic systems are used to achieve production improvements in manufacturing and healthcare.

Computer Vision:

Computer vision enables computers to understand and analyze visual information from the external environment, recognizing objects or scenes. Doctors in the healthcare environment often use this technology to identify diseases from images.

3.1.3 Language Models (LMs) and Large Language Models (LLMs)

In recent years, NLP techniques and ML algorithms have been combined to give birth to Language Models. Zhao et al. (2023) state that language modeling (LM) is a key method for enhancing machine language intelligence, enabling them to analyze large amounts of data and generate humanlike output text. The development of LMs is not new and is based on four major development milestones, according to Minaee et al. (2024) and Zhao et al. (2023):

- Statistical Language Models (SLMs). These models are based on statistical learning methods, primarily on Markov's assumption that the next word can be predicted based on the most recent context, to build the word prediction.
- Neural Language models (NLMs). These models use NPLs to predict the next words based on the aggregation of the meaning of the preceding words.
- Pre-trained language models (PLMs). These models are task-agnostic, and the word prediction is performed through the pre-training and fine-tuning of recurrent Neural Networks.
- Large language models (LLMs). LLMs are transformer-based neural language models based on scaled PLMs that aim to achieve better capabilities and capacities. Compared to PLMs, LLMs offer stronger language understanding, better generation capabilities, and more emergent capabilities.

The GPT-3 model, developed by OpenAI, was one of the first large language model (LLM) models to produce notable results in generating text that is contextually relevant to the input.

Major LLMs capabilities:

According to (Tamkin, et al., 2021), the primary capability of LLMs is the ability to understand and respond to inputs provided to them. LLMs are capable of analyzing vast data sets, identifying patterns, and producing responses that are coherent and contextually appropriate. They can generate full texts, handle translations, conduct Q&As, and engage in role-playing. LLMs exhibit human-like abilities such as natural language interaction, knowledge, memorization, and reasoning generalization. They complement these capabilities with: Reasoning Capabilities (compositional reasoning capabilities, complex task decomposition, symbolic and commonsense reasoning), Generalization Capabilities (which include length generalization, Structure Generalization, and finally, Diversification Capabilities (Role Playing, Generalization across tasks) (Li, et al., 2024).

Notable AI LLMs Models:

According to Zhao et al. (2023), in recent years, several notable AI language models have emerged, taking advantage of advancements in LLM development phases:

- Word2Vec was developed in 2013. It solves typical NPL tasks (static word representations) based on Neural LMs.
- ELMo and BERT were developed in 2018. They solve various NPL tasks (context-aware representations) based on pre-trained LMs. These models are suitable for classification and categorization.
- Chat GPT3/4 was developed in the 2020s to solve various real-world tasks (scaling LMs, prompt-based completion) based on LLMs.

3.1.4 The Case of ChatGPT

ChatGPT, developed by OpenAI based on their latest model, GPT-4o, is considered by many to be the best LM. It can generate human-like text, understand context, and provide context-relevant answers based on various inputs (OpenAI, 2023). It is considered a generative model because it cannot only understand a context (like BERT or ELMo) but also generate text, answer questions, and participate in a conversation. Its strength relies on massive datasets and millions of parameters to provide the necessary response.

The development of the GPT model is not new, as can be seen from the figure below. The first version was developed in 2018, but it was after the release of GPT-3.5 in 2022 that ChatGPT was created and made publicly available. Since then, it has only been a matter of

months before professionals at all levels in many industries widely use it.

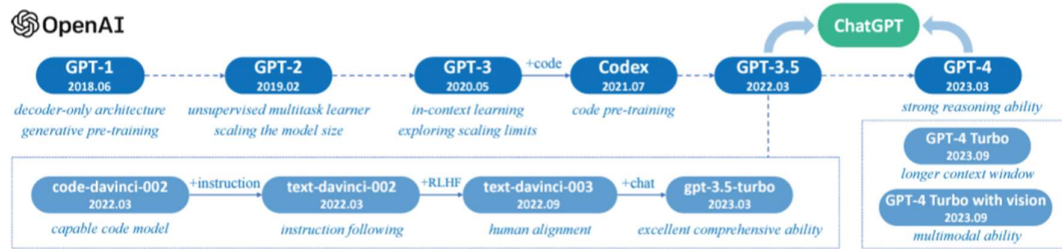


Figure 7: Evolution of GPT (Zhao et al., (2023))

ChatGPT capabilities and limitations:

ChatGPT has brought a wide range of capabilities to the people who use its services (Wiredu et al., 2023):

- Create new things: Based on the input provided, it can generate new text, images, etc.
- Enhance writing skills: Providing a text as input can enhance content that is adaptable to each case (thesis, essay, etc.).
- Translate text: It can translate input text into different languages.
- Generate code: It can translate ideas into programming languages and check the programmers' language for potential flows.
- Authentic dialogues: It can be used as a Q&A, recalling all previous interactions while its replies are human-like.
- Summarization. Given a paper as input, it can provide a summary highlighting the points provided as parameters in the input.
- Learning and enlightening. It can learn, adjust, and expand its replies through human interactions. It is expected to be very precise soon.

However, ChatGPT also has some severe constraints (Wiredu et al., 2023; Koubaa et al., 2023; Garg, 2023):

- Data Privacy and Ethics: ChatGPT relies on extensive data, making complete data privacy difficult to guarantee. Additionally, its widespread use in social media and customer service facilitates the spread of misinformation. Moreover, there is an ethical concern regarding the delegation of decision-making to AI. For instance, certain automotive manufacturers are developing vehicles that possess the capability

to make autonomous decisions, thereby highlighting the necessity for an appropriate balance to be achieved.

- Bias and Fairness: Since ChatGPT is based on language models, biased questions, LMs, and training can lead to biased responses. This can also be due to the constraint of the training data.
- Nonsensical and Wrong Answers: Sometimes, ChatGPT generates responses that are not only incorrect but also harmful. This is due to a lack of proper training. So, it is important to validate the information from consistent resources before depending entirely on the answers provided by ChatGPT.
- Lack of understanding of human thinking: Sometimes, the user must ask the same thing differently for the ChatGPT to provide an answer that matches the input context.
- Security: AI systems are targets of attacks where the inputs are manipulated.
- Regulations and compliance: As AI use increases, regulations controlling its application pose many challenges to developers.

ChatGPT applications:

ChatGPT is already being used in many domains (Koubaa et al., 2023):

- Healthcare: ChatGPT has the potential to contribute massively to the healthcare field by enhancing diagnosis, making it more precise and efficient, and reducing costs.
- Research: ChatGPT can help in the research field by providing insights and in-depth analysis.
- Education: ChatGPT can improve education quality by offering personalized content to improve learning. It is already used to solve complex mathematical exercises.
- Industry: ChatGPT has already been used for customer service and marketing purposes. It can provide efficiency, insights, and in-depth analysis.
- Financial industry: ChatGPT can analyze and predict stock data and give investment advice.

3.2 Related work on the impact of AI on performance improvement

Only three articles were found concerning the impact of AI and ChatGPT on organizational performance. Two are not directly linked to software development companies, and one is somehow relevant:

- Wamba-Taguimdje et al., 2020, Influence of artificial intelligence (AI) on firm performance: the business value of AI-based transformation projects. Wamba-Taguimdje found that implementing AI in various industries has transformed processes into being more intelligent, practical, self-reactive, and optimized, eliminating those done manually, as AI encompasses the entire value chain of the organization: R&D, maintenance, sales and marketing, production, forecasting, and services. The article also states that IT development companies utilize AI in development and testing environments to enhance productivity.
- Mikalef et al., 2021, Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. In this article, Mikalef states that although AI is adopted early, many organizations struggle to improve their performance. This is due to their need to implement AI solutions and effectively build essential AI capabilities. The most significant AI capabilities are:
 - Data: The existence and exploitation of data are important in training AI.
 - Technology: The underlying technology stack is crucial for leveraging AI.
 - Technical Skills: Ability to realize custom AI algorithms.
 - Business Skills: The knowledge of how and where AI could be applied.
 - Inter-departmental coordination: The ability to coordinate activities among departments.
 - Organizational change: The organizations' ability to perform changes to incorporate AI.

If these conditions are met, AI can significantly enhance performance by impacting key performance indicators.

- Siddiqui, 2024, The Role of AI Integration in Fostering Innovation within Software Houses: AI improves market performance and competitiveness by improving data analysis, pricing optimization, and decision-making capabilities. Dohmke et al. (2023) mention that productivity increased as users adopted AI up to 30% of the code.

3.3 Impact of AI on performance improvements in software development companies

While there are few articles discussing the influence of AI on enhancing performance within software development firms, numerous business functions where AI is currently being utilized are already affecting organizational performance:

- Software development and testing
- Project management practices and PMO
- HR processes

As such, we will examine how AI influences the respective functions.

3.3.1 Impact of AI on Project Management Practices

Hussain et al. (2023), found out that AI can improve project managers' performance by eliminating mistakes and repetitive tasks. At the same time, AI helps project managers create a reasonable schedule of activities.

AI addresses decision-making challenges with machine learning (ML) and deep learning (Odejide et al., 2024). ML analyzes historical data, identifies patterns, and suggests improvements in resource allocation, schedules, and costs. Deep learning conducts scenario simulations and offers insights by processing unstructured data. This aids project managers in their decision-making processes. For risk management, AI identifies and classifies risks based on their probability and impact, and recommends proactive measures to mitigate potential issues.

Regarding Agile project management, Ståhlberg (2024) concludes that AI can help estimate the effort required for a single task. This enables the team to plan and prioritize user stories effectively. Additionally, it has the potential to enhance the team's efficiency, as the estimation and prioritization of forthcoming tasks would require significantly less time.

Ghimire et al. (2024) state in their research that AI-driven assistants, such as Chatbots and NLP, facilitate communication and decision support, while ML techniques enable data-driven decision-making. AI systems enhance operational efficiency by automating task assignments according to skill sets and availability, while also predicting potential resource shortages and unavailability. Furthermore, they provide real-time updates and notifications and can generate concise summaries of meetings. Regarding cost and schedule management,

AI can predict budget and timeline deviations using real-time data, suggesting adjustments to meet the constraints.

AI has recently been utilized in automated project planning by analyzing the performance of past projects, intelligent resource scheduling through resource balancing, and communication by leveraging NLP for report creation, updates, and meeting minutes (Patel, 2023).

AI also helps tenders' submissions by optimizing bidding strategies and predicting costs based on historical data (Gil et al., 2021).

Russell (2024), in his research, found that AI is utilized in data management for purposes such as data analysis, documentation, and reporting to automate report generation, support decision-making, facilitate communication between stakeholders, and streamline workflows. He also discovered that in project management, AI's responses were similar to those of junior profiles.

Primary techniques that can be used (Ghimire et al., 2024 and Gil et al., 2021):

- ML is used to detect patterns and predict outcomes by analyzing vast datasets. Examples: Historical data analysis, forecasting, and risk identification.
- Neural Networks process data as the human brain does and propose decisions. Examples: risk classification and schedule optimization.
- Deep learning for processing complex data. Examples: Prediction models.
- NLP for human language generation. Examples: project documentation analysis, reporting tasks automation, and communication.
- Genetic algorithms for resource allocation.

Advantages of AI in project management (Patel, 2023):

- Increased efficiency with administrative overhead reduction.
- Improved decision-making with recommendations based on historical data.
- Efficient resource allocation with waste reduction.
- Accurate forecasting with precise timeline predictions.

3.3.2 Impact of AI on Software Development Processes

According to Siddiqui (2024) and Barenkamp et al. (2020), AI is already used in software development, automating routine tasks, analyzing big data, and testing, resulting in cost reductions and increased productivity. Also, Odeh et al. (2024) mention that automated code

generation feature usage is increasing among developers, and tools such as ChatGPT and GitHub Copilot are becoming increasingly popular. AI has also started being used in the following software phases, according to Garg (2023), Barenkamp et al. (2020), Sorte et al. (2015), Padmanaban et al. (2019), Nguyen-Duc et al. (2023), and Ståhlberg (2024):

- **Project planning:** During project planning, AI can support task assignment, resource allocation, and the creation of schedules considering cost and time constraints.
- **Requirement gathering:** AI facilitates requirements gathering using data science and machine learning techniques. Machine learning helps analyze and predict requirement dependencies, prioritize them, and assess the impact on the overall project, while data science helps with modeling problem domains. In addition, NLP techniques help transform language requirements into precise specifications, facilitating the communication between developers and stakeholders. NLP can also process unstructured data to identify hidden requirements and distinguish between functional and non-functional requirements, reducing ambiguity. SI can also simulate scenarios to identify whether the requirements reflect actual needs.
- **Problem analysis:** AI, based on machine learning and big data, can predict potential issues and outcomes, aiding in informed decision-making. Chatbots and intelligence systems can facilitate stakeholder communication by responding to questions and ensuring alignment between all parties. Finally, AI can predict risks associated with project requirements.
- **Software estimation:** Using genetic algorithms, AI can provide accurate cost and timeline estimations. Computational intelligence methods can also verify the software's readiness, ensuring the highest possible quality.
- **Software design:** AI can support the team by considering information from other projects during the software design. Neural Networks play an important role in this phase, helping architects create the necessary code and choose the appropriate designs. Intelligent design assistants can offer guidance and recommendations. AI can also validate the solutions that architects propose, ensuring the creation of scalable and performant solutions that adhere to cost and scalable constraints. AI can go even further and provide complete working prototypes based on requirements following industry standards and best practices.

- Code generation: Automatic code generators convert natural language specifications into executable code, while AI tools analyze and restructure the code, providing feedback on the provided code. LLMs can generate functional code snippets that are ready for development teams. These LLMs can also be fine-tuned for web development, game design, or back-end development.
- Bug detection: AI-based code analysis and historical information retrieval can detect potential issues and suggest bug prevention. Machine learning models can identify error-prone areas, facilitating preventive actions. AI-based static code analysis tools like SonarQube and DeepCode analyze codebases in real time to identify vulnerabilities.
- Code completion: AI-powered Integrated Development Environments offer automated code completion and suggestions, which helps developers avoid syntax errors. Developers often feed LLM systems like Codex and Copilot code to be analyzed, corrected, and completed. In addition, AI can optimize the code, providing refactoring suggestions and corrections.
- Documentation phase: Many developers already use AI to produce documentation related to a code provided.
- Deployment phase: AI models can scan the deployment environments for potential failures and suggest preventive measures. AI can also fully monitor deployment pipelines, eliminating human errors and ensuring a smooth release process by orchestrating testing, packaging, and installation processes. AI could also manage the environments' configuration, ensuring consistency and compatibility.
- Maintenance phase: NLP tools can analyze user feedback, while machine learning models can monitor deployed systems to detect failures and security breaches. AI could also suggest updates and patches to maintain system security. Furthermore, GenAI can facilitate tasks like converting monolithic systems to new technologies and legacy systems to modern programming languages.

Advantages of AI in SDLC (Padmanaban et al., 2019; Nguyen-Duc et al., 2023):

- Improved Efficiency: Repetitive tasks are eliminated. Code generation and automatic unit testing can speed up the development process.
- Enhanced Quality: AI can detect defects early.

- Cost reduction: Efficient resource allocation and refactoring proposals reduce overall project costs.
- Adaptability: AI systems can learn, adapt, and respond to changing requirements.
- Professional Competencies: GenAI can be an educational tool for novice developers, guiding them through complex tasks. Copilot, for example, mimics pair programming.
- Software Engineering Education: GenAI can be used as a reference to teach programming and software development concepts. Making them accessible to a broader audience.

In summary, according to (Padmanaban et al., 2019), the AI techniques suitable for the SDLC are:

- Neural Networks for risk prediction, bug detection, and forecasting.
- Genetic algorithms for project schedules and resource allocation.
- Fuzzy logic for uncertainty handling or testing scenarios.
- NPL is used to convert requirements to structured data and provide documentation assistance.

According to Ståhlberg (2024), the software domains that benefit most from adopting artificial intelligence include testing, as its performance demands significant resources and implementation effort. Ultimately, code generation dramatically accelerates development and enhances CI/CD processes, which can be automated, allowing for better identification and reporting of issues in real-time.

3.3.3 Impact of AI on Software Quality Assurance Processes

AI can also help with quality assurance, which directly affects performance. According to Sorte et al. (2015), generating test data using genetic algorithms can be done quickly, ensuring plurality and diversification. AI can also evaluate the test coverage, propose improvements, identify the existing gaps, and ensure quality. Regarding GUI testing, AI can assist by creating models, adapting the test cases when the GUI changes, and creating automatic scenarios simulating user behavior. Also, Hourani et al. (2019) found that AI can be used for regression testing by classifying test cases, enhancing efficiency, and detecting

faults. AI is also being used in the following quality assurance areas, according to Batarseh et al. (2020), Khan et al. (2024), and Lima et al. (2020):

- Test case generation: NLP and genetic algorithms can generate test cases based on the specifications.
- Fault prediction: ML models can automatically identify discrepancies between specifications and development and point out error-prone areas.
- Requirement Analysis: AI can analyze the requirements and complete missing test cases.
- Performance testing: AI models can predict the software's behavior under load or stress conditions and propose performance optimizations. They can also identify bottlenecks and enable proactive reactions.
- Test Case Prioritization: AI can classify test cases based on their likelihood of failure and propose the appropriate resource allocations.
- Test Maintenance: AI simplifies the maintenance of the testing scripts, adapting them to the application's changes.
- Black-Box Testing: AI techniques are especially effective because they can analyze large datasets without the need to access to the source code.
- Regression Testing: AI is used to prioritize test cases based on their historical performance, execution time, and error frequency.
- Optimization: AI is widely used to optimize the testing process. For instance, to cluster techniques group similar test cases, simplifying execution.

Benefits of using AI in testing (Hourani et al., 2019, Islam Khan, et al., 2024):

- Efficiency: Automatic test generation reduces time and resources, thus minimizing cost.
- Accuracy: AI minimizes human errors.
- Scalability: AI can handle complex systems and extensive test data, thus achieving the agreed coverage.
- AI automates repetitive tasks, and as a result, operational costs are reduced, and the delivery time to the market is less.
- AI ensures that the target testing coverage is achieved and can adapt the test cases according to the changing requirements.

3.3.4 Impact of AI on Human Resource Processes

According to George & Thomas (2019), the primary use of AI in human resource processes is talent acquisition. It can be used to screen resumes, conduct assessments, and select suitable candidates, thereby eliminating over 75% of manual work. It can also provide candidates with immediate feedback following interviews. Intelligent chatbots could manage the onboarding process to facilitate newcomer orientation. AI could also engage employees by generating personalized objectives and implementing a feedback system that analyzes the inputs (Hemalatha et al., 2021). NLP could enhance HR processes by screening resumes and improving communication between professionals. Machine vision could help understand candidates' behavior during interviews, while AI could generally handle automation tasks, such as interview scheduling.

AI could also minimize bias by offering data-driven assessments in candidate evaluations, as well as provide administrative efficiency through automated routine tasks. Yawalkar (2019) highlights the potential for AI to improve administrative efficiency. By automating routine tasks, AI eases HR administrative burdens, allowing HR professionals to focus on strategic initiatives. AI also aids in bias reduction by delivering data-driven assessments in candidate evaluations and job descriptions. He notes that AI algorithms accelerate the identification of suitable candidates based on specific skill sets, thus shortening hiring cycles. Lastly, AI enhances engagement and satisfaction through predictive tools and real-time interactions. Bujold et al. (2024) assert that AI could assist in performance evaluation by aggregating performance metrics, feedback, and behavioral data to provide a comprehensive view of employee performance and productivity.

3.3.5 Challenges Applying Artificial Intelligence

According to Russel (2024), the significant challenges of applying AI in project management are the lack of response quality, contextual depth, and output bias.

According to Nguyen-Duc et al. (2023), the significant challenges are the lack of alignment between the generated content and user requirements, the output biases based on training data biases, and the integration of GenAI into existing workflows. According to Padmanaban et al. (2019), the main challenges are the skill gap that the development teams face in efficiently utilizing AI and the dependency on the amount and quality of data. The same is observed in the Human Resource domain (Yawalkar, 2019). He also mentions that

HR professionals usually lack the necessary skills to adopt and learn AI tools and require good managerial skills.

Fan et al. (2023) in their paper mention that the plausible but incorrect outputs that AI produces pose a risk to critical systems. Furthermore, AI's code often contains vulnerabilities due to an incomplete understanding of the latest best security practices. AI's non-deterministic output complicates improvement assessment over traditional tools. Khaliq et al. (2022) highlight that integrating AI into existing workflows is costly and time-consuming, while interpreting AI results for different stakeholders is also a significant issue. Hemalatha et al. (2021) also state that HR professionals are resistant to change and believe that AI will lead to job losses. To avoid this, organizations will need to redefine HR roles. Ajiga et al., (2024) mention that AI adoption requires substantial investment, including tools, training, and infrastructure. Additionally, the complexity of AI models and their integration with legacy systems present technical challenges. Chowdhury et al. (2023) came to the same conclusion: The lack of AI transparency regarding its outputs, the challenge of integrating modern AI tools with legacy HR systems, and the fact that AI is not yet fully autonomous in HRM processes hinder its adoption.

Bento et al. (2022) state that using AI in project management presents significant challenges; however, ongoing research indicates that companies acknowledge its potential. Mohammad & Chirchir (2024) highlight the vast amount of data required for training, the high costs, the highly skilled personnel, and difficulties with system integration and interoperability as major barriers when considering AI for project management purposes.

3.4 Summary

The existing literature indicates that AI has already begun contributing to organizational performance factors, and this trend is expected to continue, particularly in software development industries. The majority of the research performed after 2022, when ChatGPT was made publicly available, indicates a rapid adoption of AI across different business sectors. While AI's role in software development is more advanced, its integration into software testing, HR processes, and project management practices is still evolving.

AI can automate repetitive tasks, improve decision-making, and optimize resource use, leading to significant gains in efficiency, accuracy, and cost-effectiveness. Nevertheless, despite its ability to enhance performance, adopting AI presents substantial challenges. Organizations encounter obstacles like knowledge deficit, lack of confidence in data,

integration difficulties, and biased AI outputs. Moreover, implementing AI demands considerable financial investment, infrastructure enhancements, and cultural shifts among staff.

While existing literature thoroughly details the theoretical benefits and potential downsides of integrating Artificial Intelligence (AI) in software development companies, a significant gap persists: the lack of empirical studies measuring the actual adoption of AI among professionals and how they perceive the benefits it is supposed to bring. Numerous studies consistently emphasize the potential for enhanced efficiency, improved quality, and more effective resource allocation. Nevertheless, the extent to which these benefits translate into tangible results in actual software development remains to be investigated. Furthermore, subjective evidence and initial observations suggest that the integration and effective utilization of AI have not advanced as rapidly as many industry experts anticipated. This disparity between expected advantages and observed outcomes underscores the pressing requirement for this empirical research.

Moreover, the difficulties faced during AI implementation in areas such as project management, human resources, and quality assurance necessitate deeper analysis. While many general challenges, such as skill shortages, data dependence, and integration issues, appear to be shared, they still need to be verified in software development companies. Current literature offers limited insight into how project management processes and HR demands affect successful AI deployments. Similarly, practical difficulties faced when using AI for quality assurance, beyond theoretical discussions, are not sufficiently investigated.

This study aims to address these significant gaps by conducting a focused analysis of the impact of AI on the performance of software development companies. By empirically examining its effects on various domains that affect performance, specifically productivity, software quality, HR practices, and project management, this research aims to deliver robust, data-driven results. The thesis aims to go beyond mere theoretical discussions, providing a comprehensive understanding of how AI genuinely contributes to both the operational efficiency and strategic effectiveness of software development companies. Ultimately, this study strives to close the gap between expectations and reality.

4. Methodology and Research Approach

This section describes the design of the research study, including the steps of the process, the research questions, and the methods for collecting and analyzing data to support the scientific hypothesis.

4.1 Research Hypotheses

Various industries now integrate AI into their daily operations, with numerous software development professionals leveraging its capabilities throughout the software development lifecycle to accelerate task completion. However, it is interesting to investigate how AI can contribute to the performance improvement of software development companies, as performance is directly dependent on productivity, quality, and efficient processes, such as HRM and project management.

The literature review revealed that AI is being increasingly adopted across various aspects of software development, with potential impacts on productivity, quality, HR, and project management. However, the degree of these impacts and the effectiveness of AI adoption remain unclear. Based on the identified potential benefits and challenges, this study proposes the following hypotheses to empirically investigate the impact of AI on software development company performance:

Table 1: Hypotheses and expected outcomes.

Hypothesis	Expected Result	Justification
How does AI impact the productivity of software development teams? Chapter 3.3.2 examines how artificial intelligence automates routine tasks, generates code, and completes coding assignments, thereby directly influencing developer productivity.	A high score is expected, with a higher score among junior professionals.	The literature (Siddiqui, 2024; Barenkamp et al., 2020; Odeh et al., 2024) consistently demonstrates that AI enhances productivity. As a result, it's reasonable to anticipate a generally favorable view of AI's influence on productivity. Additionally, the literature notes that junior developers often invest more time in repetitive coding tasks, syntax checking, and mastering best practices. In contrast, senior developers, having more experience,

		may have already streamlined their workflows, leading them to perceive a less significant increase in productivity (Russell, 2024).
What role does AI play in improving the Quality (software testing phase)? This directly refers to AI use in quality assurance (3.3.3) and highlights both efficiency and effectiveness.	A high score is expected among Software development company professionals.	The literature (Sorte et al., 2015; Hourani et al., 2019; Khan et al., 2024) highlights AI's capability for QA tasks. AI's ability to achieve more excellent test coverage and adjust test cases to meet evolving requirements further supports the expected high score.
How does AI influence HR practices in software companies? Chapter 3.3.4 covers the use of AI in talent acquisition, candidate assessment, and performance evaluation.	The medium score is expected, considering the medium adoption of usage in the HR industry.	While AI can streamline many HR tasks, the HR process involves intricate human interactions and strategic decision-making that AI cannot fully replicate (George & Thomas, 2019; Yawalkar, 2019). Furthermore, the literature points out concerns regarding AI bias in HR (Yawalkar, 2019). The average score suggests that the use of AI in the HR sector is behind its progress in software development.
To what extent does AI enhance project management practices? Chapter 3.3.1 covers AI's applications in scheduling, resource allocation, risk management, and communication. s	A medium score is expected, considering the medium adoption of AI in the day-to-day activities of PM professionals.	AI can provide valuable insights for project management (Hussain et al., 2023; Ghimire et al., 2024), but project management also relies on human judgment, stakeholder communication, and adaptability. Therefore, a moderate improvement is expected. The literature also highlights challenges like lack of contextual

		understanding, output bias, and integration difficulties (Russell, 2024; Mohammad & Chirchir, 2024). The survey should reveal these limitations.
How could AI be better adopted by software development companies? Chapter 3.3.5 outlines the various challenges associated with AI adoption.	Companies are not mature enough to fully exploit AI capabilities.	The literature (Nguyen-Duc et al., 2023; Padmanaban et al., 2019; Ajiga et al., 2024) consistently identifies skill gaps, data quality issues, and integration challenges as significant barriers to AI adoption. It is logical to expect that many companies are still in the early stages of AI adoption, and have not yet fully addressed these barriers

4.2 Research Design

The design consists of a survey that targets professionals working in software development companies. It was disseminated to 5 multinational software development companies, primarily involved in projects for the European public sector, although some also work on projects in the private sector. Most of them are medium- or large-sized companies that have more than 200 employees, as these are the ones that can afford to adopt AI more easily. The survey also aimed to include smaller companies to provide a broader range of answers. The survey primarily targeted senior profiles, as they have the experience to better judge AI's contribution to operational performance. Finally, the questionnaire was distributed to approximately 200 professionals representing a diverse range of fields. Questions of different types will test each hypothesis according to the following table:

Table 2: Research Design

Research Question	Question Numbers
1. How does AI impact the productivity of software development teams?	5,6, 7, 8, 9,10
2. What role does AI play in improving the quality (software testing phase)?	11,12,13,14
3. How does AI influence HR practices in software companies?	15, 16, 17

4. To what extent does AI enhance project management practices?	18,19,20
5. How could AI be better adopted by software development companies?	21,22, 23,24,25

The questionnaire has the following types of questions:

- Demographic Questions:
 - What is your role in your organization?
 - How many years of experience do you have in the software development industry?
 - How many employees does your company have?
 - Does your organization currently use AI tools in its operations?
- Questions related to productivity and performance:
 - How frequently do you use AI tools in your day-to-day work?
 - Do you agree that AI has reduced the time required for code generation, code completion and code proposals?
 - Do you agree that AI has improved team collaboration?
 - Do you agree that AI has improved the accuracy of task estimations in your team?
 - What is the most significant area of software development that AI could improve?
 - Do you agree that AI supports innovation in software development industry?
- Questions related to quality and performance:
 - Do you agree that AI is efficient in identifying critical bugs during testing?
 - Do you agree that AI impacts the speed of regression testing in your projects?
 - Does the use of AI in software testing improve test coverage?
 - Do you agree that AI-generated quality reports are better than manual-generated ones?
- Questions related to HR practices and performance:
 - Do you agree that AI has supported your organization's recruitment processes (reducing bias, screening cv, etc)?
 - Do you agree that AI has impacted the onboarding processes in your organization?

- Do agree that AI contributes to monitoring and improving employee performance metrics?
- Questions related to PM practices and performance:
 - Do you agree that AI has helped identify project risks?
 - Do you agree that AI facilitates the generation of project timelines and schedules?
 - Do you agree that AI has facilitated communication between project stakeholders?
- Questions related to AI adoption:
 - What are the primary challenges in integrating AI into the software development lifecycle?
 - What are the main motivations for adopting AI in your organization?
 - Do you agree that your organization is ready to adopt AI?
 - Do you agree that top management's support is important for successful AI adoption?
 - Do you agree that your organization will increase its investment in AI in the next two years?

4.3 Data Collection

A sampling approach was selected to conduct this research. The aim was to gather a diverse range of professionals, each with varying levels of experience and engagement in different phases of software development. Data were collected using social network platforms, such as LinkedIn, and corporate channels. This resulted in around 108 responses.

4.4 Data Analysis

Various statistical techniques were employed to analyze the data, including analysis of variance, while means and standard deviations were used to draw conclusions. Correlation analysis was conducted to examine the relationships among various variables.

4.5 Methodology

For this research, the quantitative method was adopted due to the larger sample size and the fact that it offers a more straightforward analysis, allowing for data comparable to similar research. The Likert scale also facilitates more effective data analysis.

4.6 Reliability and Limitations

The research was conducted anonymously, with straightforward questions designed to cover the subject under investigation. Additionally, statistical models were employed to analyze the results and identify patterns. Experienced professionals were targeted for this research due to their better understanding of performance in the software development industry.

On the limitations side, the study's size may not be adequate to provide a comprehensive and representative picture, as software development performance is influenced by numerous factors and dimensions that are not covered by this research. Different organizational and managerial structures can influence and affect the use of AI in software companies, for example. Additionally, participants could provide biased answers, as their responses might reflect their desires rather than reality. Biased answers could also be provided due to the different interpretations of the questions among participants.

During data analysis, researchers' opinions and visibility could influence the interpretation of the data, even though statistical analysis could act as a countermeasure.

5. Findings

5.1 Descriptive Statistics

Two significant actions were performed on the dataset to make the results easily analyzed: Variables were assigned to questions, and the dataset was cleaned (Appendix 2 presents this process). The questionnaire targeted professionals working in software development companies, whose roles varied. A grouping was made to facilitate the processing of the results. Out of 108 responses, one was completely blank and was removed from the dataset. Jasp was used as a tool to perform the required analysis.

5.1.1 Job Role

Table 3: Job Role Distribution

Variable		Counts	Total	Proportion
Role	Engineer	62	107	0.579
	HR Professional	8	107	0.075
	Manager	5	107	0.047
	Project Manager	20	107	0.187
	Quality Assurance Specialist	12	107	0.112

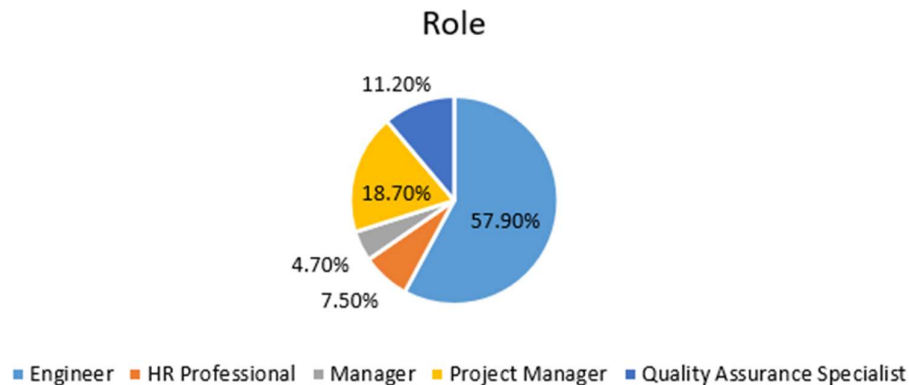


Figure 8: Job Role Distributions.

The majority of participants were engineers (57.9%), which is expected since the majority of employees in software development companies are software engineers. Project managers made up approximately 18.7%, Quality Assurance Specialists 11.2%, HR Professionals 7.5%, and Managers 4.7%.

5.1.2 Experience

Table 4: Experience Distribution (Jasp Analysis)

Variable		Counts	Total	Proportion
Experience	Less than 1 year	3	107	0.028
	1-5 years	23	107	0.215
	6-9 years	38	107	0.355
	More than 10 years	43	107	0.402

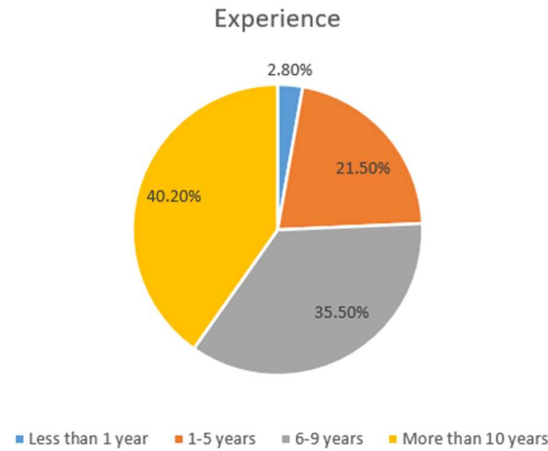


Figure 9: Experience Distribution.

We can observe that most participants had more than 10 years of experience (40.2%), followed by those with between 6 and 9 years of experience (35.5%). 21,5% had between 1 and 5 years, and 2,8% had less than a year.

5.1.3 Company size

Table 5: Company size distribution (Jasp Analysis)

Variable		Counts	Total	Proportion
Company_size	Fewer than 50	5	107	0.047
	50-200	28	107	0.262
	201-500	23	107	0.215
	More than 500	51	107	0.477

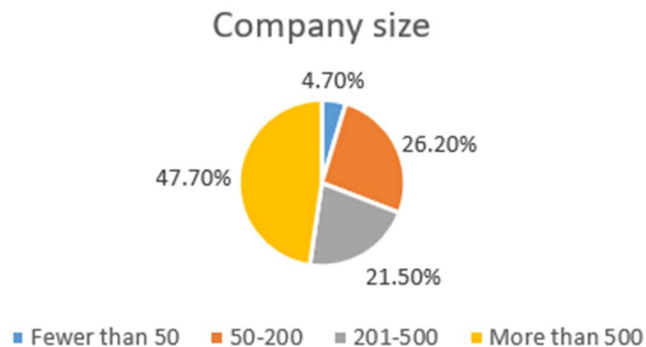


Figure 10: Company_size Distribution.

Almost half of the participants (47,7%) work for companies with more than 500 employees. In total, only 4,7% of the participants work in small companies (fewer than 50 employees).

5.1.4 Frequency of AI Usage

Table 6: Frequency of AI usage (Jasp Analysis)

Variable		Counts	Total	Proportion
PR_Frequency	Not at all	6	107	0.056
	Rarely (1 -2 times per month)	12	107	0.112
	Occasionally (Several times per month)	25	107	0.234
	Regularly (3- 4 times per week)	36	107	0.336
	Always (every day)	28	107	0.262

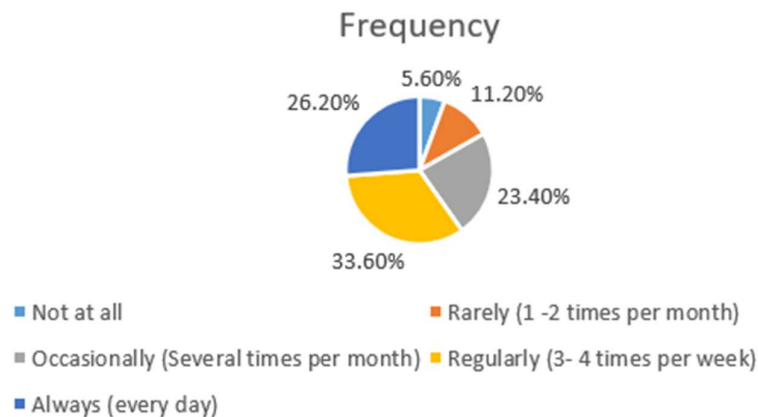


Figure 11: PR_Frequency Distribution.

We observe that only 26,2% of the participants use AI every day in their daily work, while another 33,6% use AI regularly. The rest, 40,2%, of the professionals do not use it often (5,6% not at all). We can also observe that although professionals in software development companies adopt AI, only 59,8% use it weekly for performance improvement.

5.1.5 AI Adoption

Table 7: AI adoption (Jasp Analysis)

Variable	Counts	Total	Proportion
AI_usage	yes	107	0.710
	no	107	0.290

We observe that out of 107 participants, 29% stated that their organization does not use AI, while 71% stated that their organization has adopted the use of AI.

5.2 Descriptive statistics of dependent variables

Several facets of its influence were evaluated as dependent variables to understand how AI affects performance. Appendix 2 presents these variables.

5.2.1 PM Variables

The figures below represent the distribution of professionals' responses regarding PM variables:

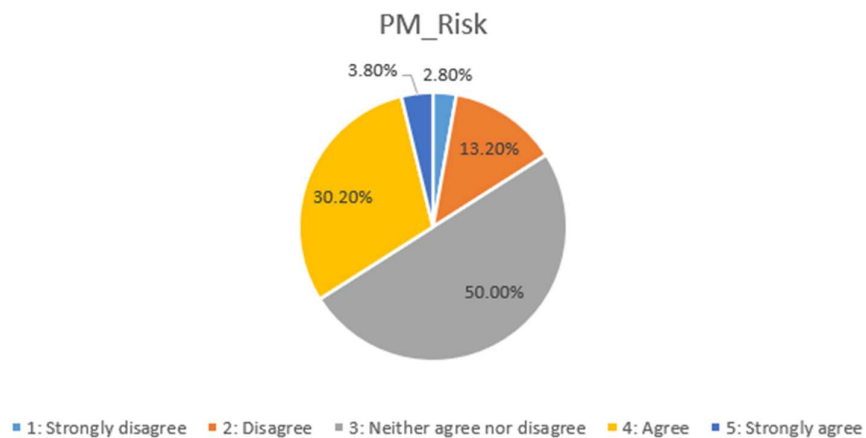


Figure 12: PM_Risk Distribution.

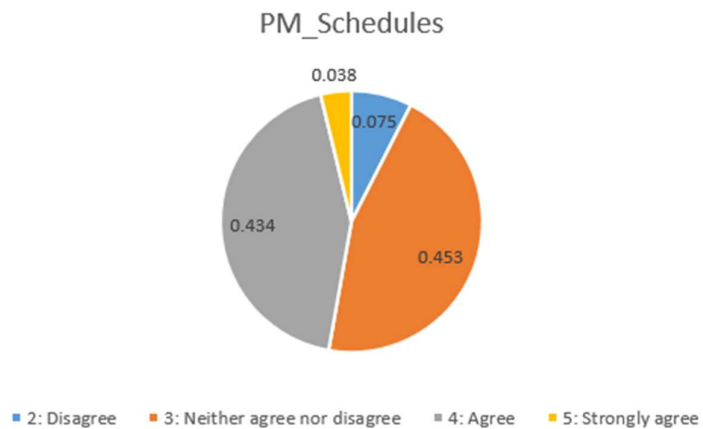


Figure 13: PM_Schedules Distribution.

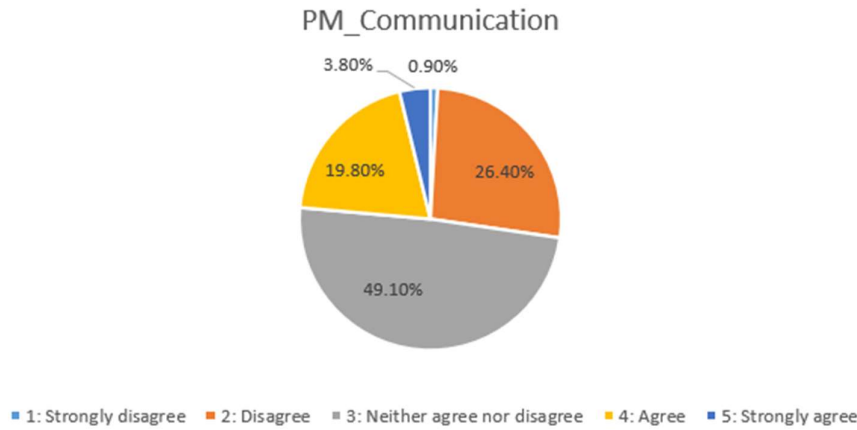


Figure 14: PM_Communication Distribution.

Table 8: Project management variables analysis (Jasp Analysis)

Entire Sample	PM_Risks	PM_Schedules	PM_Communication
Valid	106	106	106
Missing	1	1	1
Mean	3.189	3.434	2.991
Std. Deviation	0.818	0.690	0.811

With one missing value, here is what we can observe:

PM_Risks: The average is 3.189 on a scale of 1 to 5. This indicates that the participants cannot conclude that AI helps with risk identification (maybe it has the potential to do so). The standard deviation of 0.818 demonstrates variability in the responses.

PM Schedules: The average rating is 3.434 on a scale of 1 to 5. This suggests that the participants believe AI can have a positive impact on planning and timelines. The standard deviation is 0.690, which is small.

PM_Communication: The average is 2.991 on a scale of 1 to 5. This indicates that the participants think AI does not contribute positively to stakeholder communication. The standard deviation is 0.811, indicating variability in the responses.

It is also interesting to examine the perception of PM professionals concerning the PM variables and how often they use AI in their day-to-day work:

Table 9: PM professionals' variable analysis (Jasp Analysis)

PM Professionals	PM_Risks	PM_Schedules	PM_Communication
Valid	20	20	20
Missing	0	0	0
Mean	3.300	3.700	3.000
Std. Deviation	0.979	0.657	0.918

Table 10: PM professional's AI usage (Jasp Analysis)

Variable	Counts	Total	Proportion
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PR_Frequency	Not at all	3	20	0.150
	Rarely (1 -2 times per month)	3	20	0.150
	Occasionally (Several times per month)	4	20	0.200
	Regularly (3- 4 times per week)	2	20	0.100
	Always (every day)	8	20	0.400

With twenty registered responses relevant to project management, we observe that the PM profiles believe that AI can contribute to identifying risks and creating project schedules (averaging 3.3 and 3.7, respectively). At the same time, they cannot express any opinion of its utility in the stakeholders' communication. Of the twenty project management professionals, 40% use AI daily, while 70% have incorporated AI into their tasks.

5.2.2 HR Variables

The figures below represent the distribution of professionals' responses regarding HR variables:

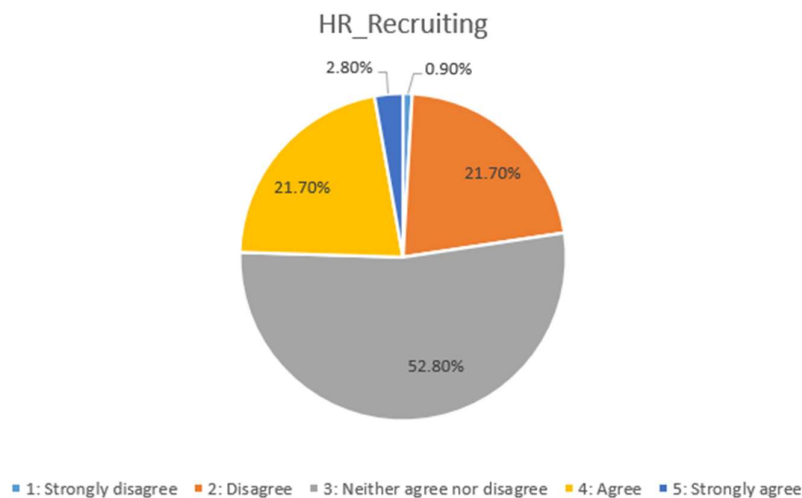


Figure 15: HR_Recruiting Distribution.

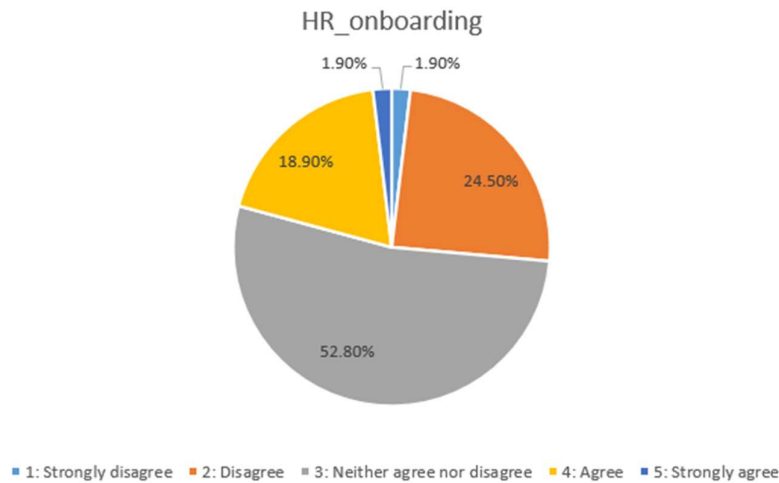


Figure 16: HR_onboarding Distribution.

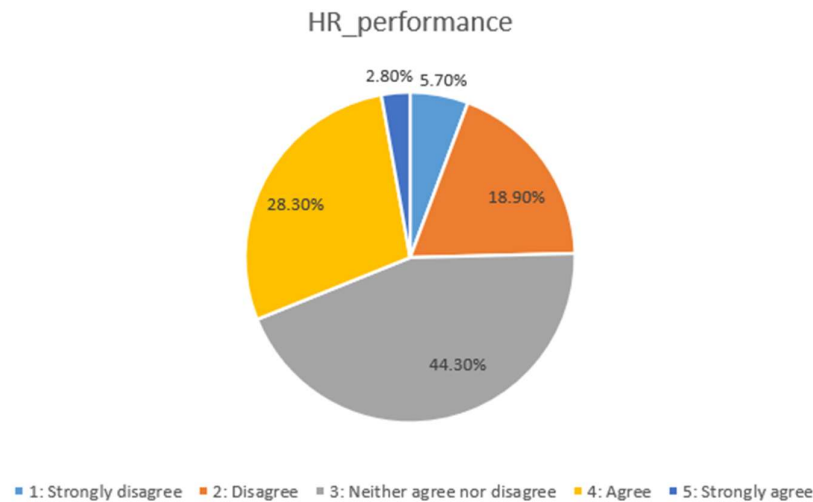


Figure 17: HR_performance Distribution.

Table 11: Human Resource Variable Analysis (Jasp Analysis)

Entire Sample	HR_recruiting	HR_onboarding	HR_performance
Valid	106	106	106
Missing	1	1	1
Mean	3.038	2.943	3.038
Std. Deviation	0.767	0.766	0.904

With one missing value, here is what we can observe:

HR_recruiting: The average is 3.038 on a scale of 1 to 5. This indicates that the participants do not think AI contributes positively to recruitment processes. The standard deviation is 0.767, which is considered small.

HR_onboarding: The average is 2.943 on a scale of 1 to 5. This suggests that the participants believe AI does not make a positive contribution to HR onboarding processes. The standard deviation is 0.766, which is considered small.

HR_performance: The average is 3.038 on a scale of 1 to 5. This suggests that the participants are unable to express an opinion on how AI positively contributes to HR performance evaluation processes. The standard deviation is 0.904, indicating a more significant variation. This means that the responders had more diverse opinions.

It is also interesting to examine the perception of HR professionals concerning the HR variables and how often they use AI in their day-to-day work:

Table 12: HR professionals' Variable analysis (Jasp Analysis)

HR Professionals	HR_recruiting	HR_onboarding	HR_performance
Valid	8	8	8
Missing	0	0	0
Mean	3.125	2.750	3.250
Std. Deviation	0.835	0.707	0.707

Table 13: HR professionals' AI usage (Jasp Analysis)

Variable		Counts	Total	Proportion
PR_Frequency	Not at all	2	8	0.250
	Rarely (1 -2 times per month)	1	8	0.125
	Occasionally (Several times per month)	1	8	0.125
	Regularly (3- 4 times per week)	3	8	0.375
	Always (every day)	1	8	0.125

With eight valid responses, we observe that HR Professionals disagree that AI helps with onboarding. At the same time, they are not confident that AI contributes positively to improvements in HR recruitment and performance evaluation despite regularly using it. From the results, it can be concluded that only 50% of HR professionals have adopted the frequent use of AI.

5.2.3 Productivity Variables

The figures below represent the distribution of professionals' responses regarding productivity variables:

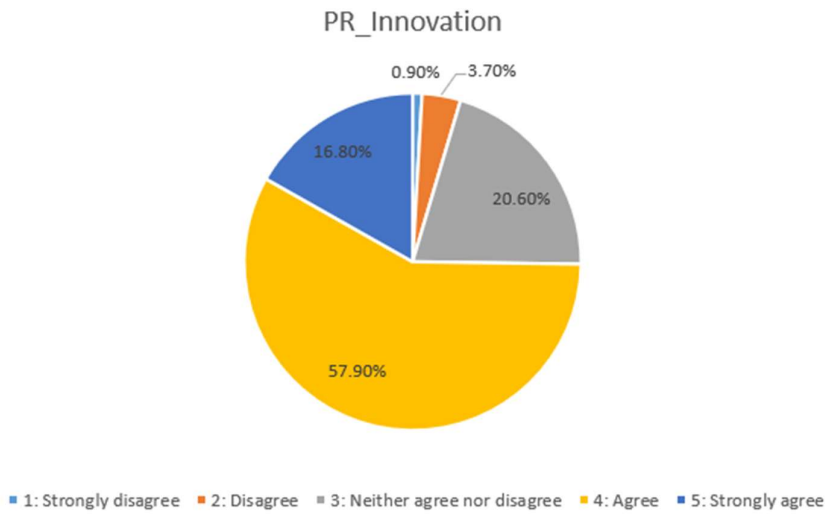


Figure 18: PR_Innovation Distribution.

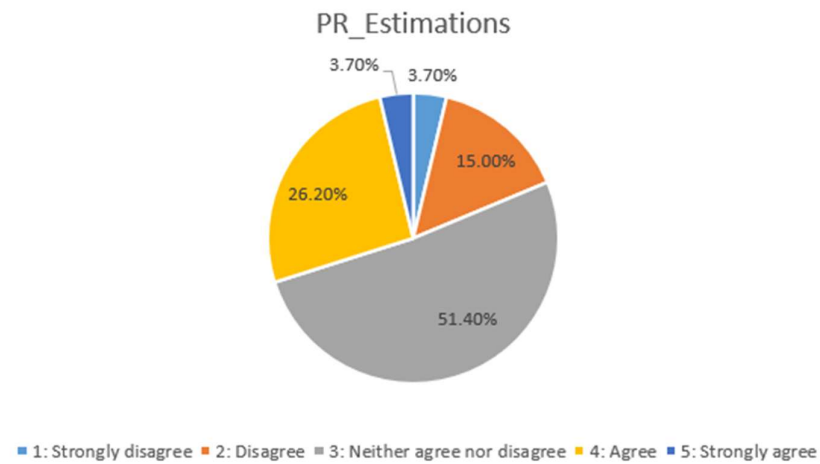


Figure 19 PR_Estimations Distribution.

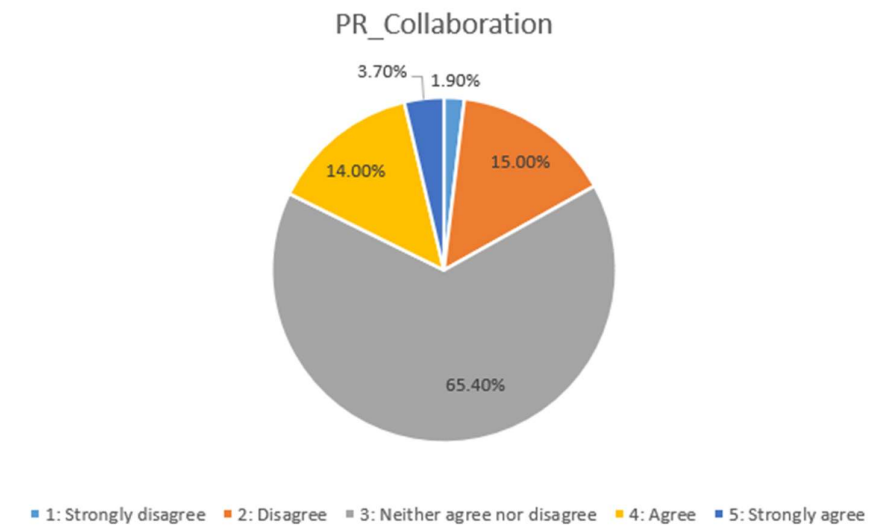


Figure 20: PR_Collaboration Distribution.

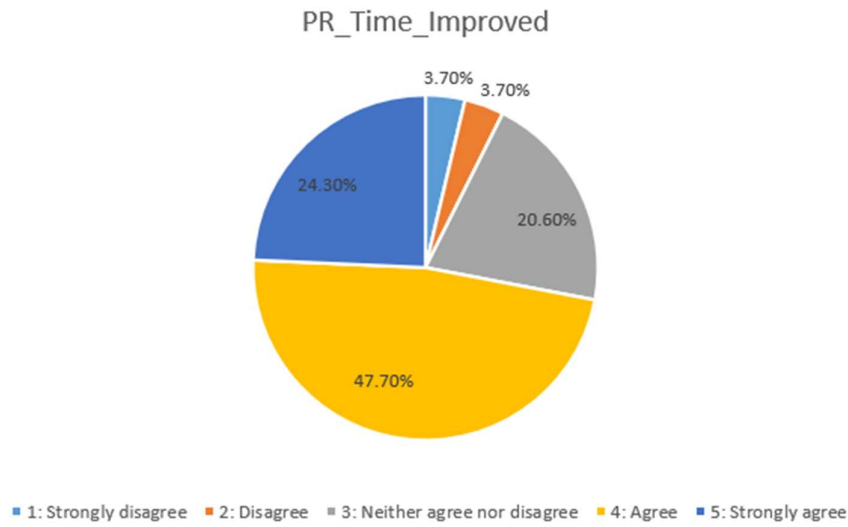


Figure 21: PR_Time_Improved Distribution.

Table 14: Productivity variable analysis (Jasp Analysis)

Entire Sample	PR_Innovation	PR_Estimations	PR_Collaboration	PR_Time_improved
Valid	107	107	107	107
Missing	0	0	0	0
Mean	3.860	3.112	3.028	3.850
Std. Deviation	0.770	0.839	0.720	0.960

Here is what we can observe:

PR_Innovation: The average score is 3.860 on a scale of 1 to 5, indicating that participants believe AI contributes to innovation. The standard deviation is 0.770.

PR_Estimations: The average is 3.112 on a scale of 1 to 5. This suggests that the participants believe AI could positively impact task estimations. The standard deviation of 0.839 demonstrates variability.

PR_Collaboration: The average is 3.028 on a scale of 1 to 5. This indicates that the participants think AI does not contribute positively to team collaboration. The standard deviation is 0.720.

PR_Time_improved: The average is 3.850 on a scale of 1 to 5. This indicates that the participants believe that AI contributes positively to completion time. The standard deviation is 0.960, indicating variability in the responses.

It is also interesting to examine the Engineers' perception of the productivity variables and how often they use AI in their day-to-day work:

Table 15: Engineers' Variable Analysis (Jasp Analysis)

Engineers	PR_Estimations	PR_Innovation	PR_Collaboration	PR_Time improved
Valid	62	62	62	62
Missing	0	0	0	0
Mean	3.048	3.790	2.887	3.887
Std. Deviation	0.895	0.832	0.749	0.977

Table 16: Engineer's AI usage (Jasp Analysis)

Variable		Counts	Total	Proportion
PR_Frequency	Rarely (1 -2 times per month)	4	62	0.065
	Occasionally (Several times per month)	19	62	0.306
	Regularly (3- 4 times per week)	25	62	0.403
	Always (every day)	14	62	0.226

We observe that most Engineers agree that AI contributes positively to innovation and time improvement (average 3.790 and 3.887), although variances exist. However, they do not think AI improves team collaboration or estimations.

We also observe that more than 60% of engineers utilize AI multiple times a week in their daily operations, but only 22.6% use it daily. We also observe that no engineer is not using AI at all.

Finally, concerning the domains where AI could improve, here are the results:

Table 17: AI Improvement Areas (Jasp Analysis)

Variable		Counts	Total	Proportion
PR_Improvement	All areas	1	106	0.009
	Coding	40	106	0.377
	Deployment	1	106	0.009
	Documentation	18	106	0.170
	N/A	1	106	0.009
	Planning	6	106	0.057
	Requirements gathering	17	106	0.160
	Testing	22	106	0.208

We can observe that, although engineers tend to agree that AI has helped them speed up their development tasks, they still believe that AI should improve in producing code that is more consistent with the context, generating more complete documentation, and enhancing testing capabilities.

5.2.4 QA Variables

The figures below represent the distribution of professionals' responses regarding productivity variables:

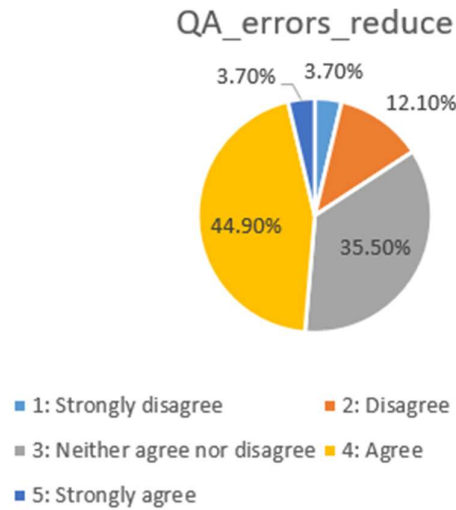


Figure 22: QA_errors_reduce Distribution.

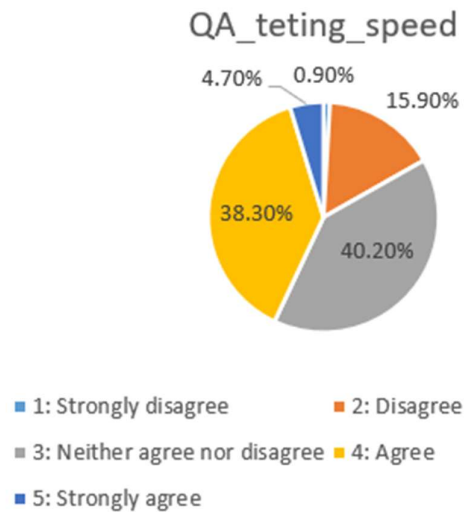


Figure 23: QA_testing_speed Distribution.

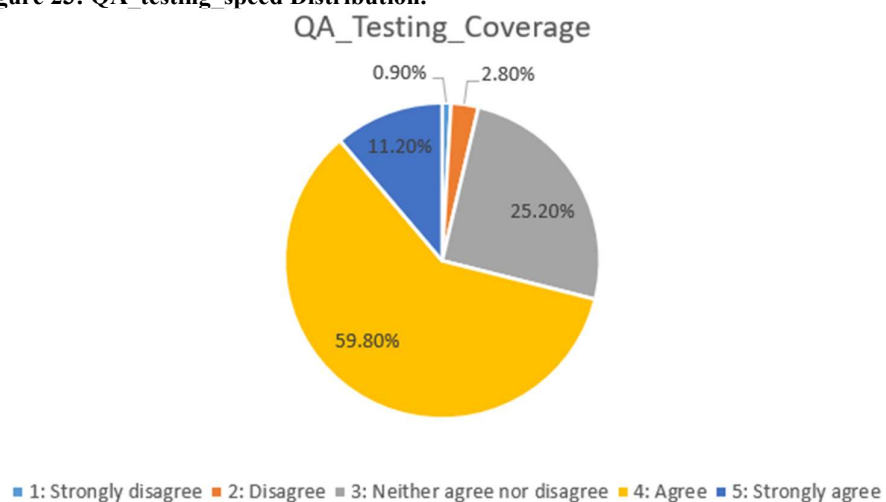


Figure 24: QA_Testing_Coverage Distribution.

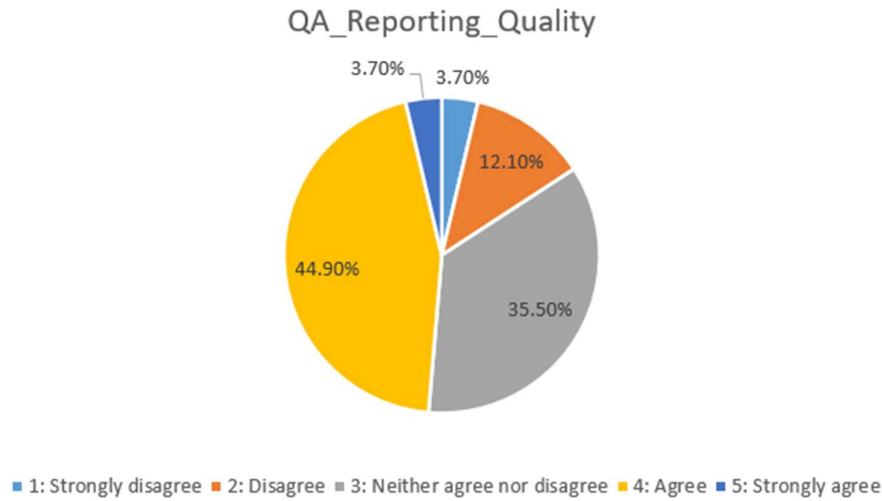


Figure 25: QA_Reporting_quality Distribution.

Table 18: Quality Assurance Variable Analysis (Jasp Analysis)

Entire Sample	QA_Errors_reduce	QA_Testing_Speed	QA_Testing_Coverage	QA_Reporting_quality
Valid	107	107	107	107
Missing	0	0	0	0
Mean	3.327	3.299	3.776	3.364
Std. Deviation	0.877	0.827	0.718	0.862

QA_Errors_reduce: The average score is 3.327 on a scale of 1 to 5, indicating that participants believe AI contributes to bug identification. The standard deviation is 0.877.

QA_Testing_Speed: The average is 3.299 on a scale of 1 to 5. This suggests that the participants believe AI could positively impact the execution of the regression tests. The standard deviation is 0.827.

QA_Testing_Coverage: The average is 3.776 on a scale of 1 to 5. This indicates that the participants think AI contributes to testing coverage completion. The standard deviation is 0.718.

QA_Reporting_quality: The average is 3.364 on a scale of 1 to 5. This indicates that the participants believe that AI contributes positively to report generation. The standard deviation is 0.862.

It is interesting to examine the QA professional's point of view concerning Quality:

Table 19: QA professionals' variable analysis (Jasp Analysis)

Quality Assurance Specialist	QA_Errors_reduce	QA_Testing_Speed	QA_Testing_Coverage	QA_Reporting_quality
Valid	12	12	12	12
Missing	0	0	0	0
Mean	2.750	2.917	3.583	3.167

Std. Deviation	0.754	0.996	0.793	1.030
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We observe some interesting results. QA professionals think that AI only contributes to testing coverage completion, while they disagree with the claim that AI can help identify bugs or increase regression testing speed. This also demonstrates that the entire sample and the QA professionals have different perceptions of how AI can contribute positively to testing activities.

Table 20: QA professionals' AI usage (Jasp Analysis)

Variable		Counts	Total	Proportion
PR_Frequency	Not at all	1	12	0.083
	Rarely (1 -2 times per month)	2	12	0.167
	Occasionally (Several times per month)	5	12	0.417
	Regularly (3- 4 times per week)	4	12	0.333

We also observe that only 33.3% of QA professionals use AI weekly, but none of the participants use it daily. Thus, it appears that AI is not integrated into the daily tasks of QA professionals.

5.2.5 Managers' Results

It is also interesting to analyze the different domains from the managers' point of view:

PM variables:

Table 21: Manager's analysis concerning PM Variables (Jasp Analysis)

<i>PM variables</i>	PM_Risks	PM_Schedules	PM_Communication
Valid	5	5	5
Missing	0	0	0
Mean	3.600	3.400	3.400
Std. Deviation	0.548	1.140	1.140

Most of the Managers who participated in the research believe that AI contributes positively to risk identification, schedule drafting, and communication among stakeholders. We also observe that apart from risk identification, the standard deviation is high for the other two variables, demonstrating variability among executives.

HR variables:

Table 22: Manager's analysis concerning HR Variables (Jasp Analysis)

<i>HR variables</i>	HR_recruiting	HR_onboarding	HR_performance
Valid	5	5	5
Missing	0	0	0

Mean	2.400	3.200	3.400
Std. Deviation	0.548	0.837	0.548

Most managers believe that AI contributes positively to onboarding processes and performance evaluation, while they disagree that AI contributes positively to recruiting processes. We also observe small response variability. This result also indicates that executives do not yet fully understand the importance of using AI in the recruiting process (for example, screening the CVs).

Productivity variables:

Table 23: Manager's analysis concerning Productivity Variables (Jasp Analysis)

<i>Productivity variables</i>	PR_Time_improved	PR_Collaboration	PR_Estimations	PR_Innovation
Valid	5	5	5	5
Missing	0	0	0	0
Mean	4.200	3.400	2.800	4.200
Std. Deviation	0.837	0.894	0.837	0.447

Most managers believe that AI contributes positively to innovation, task execution time, and team collaboration, while they disagree that AI is helpful with estimations. There is also medium variability among the responses.

QA variables:

Table 24: Manager's analysis concerning QA Variables (Jasp Analysis)

<i>QA variables</i>	QA_Errors_reduce	QA_Testing_Speed	QA_Testing_Coverage	QA_Reporting_quality
Valid	5	5	5	5
Missing	0	0	0	0
Mean	4.000	3.600	4.200	3.200
Std. Deviation	0.707	1.140	0.447	0.837

Most Managers believe that AI contributes to all QA variables, especially bug detection, testing coverage completion, and regression testing speed. All the variables present medium to low variability except for regression testing speed, which has high variability. There is also different perception between QA professionals and managers.

5.2.6 AI Adoption and Challenges

The figures below represent the distribution of professionals' responses regarding AI's Adoption variables:

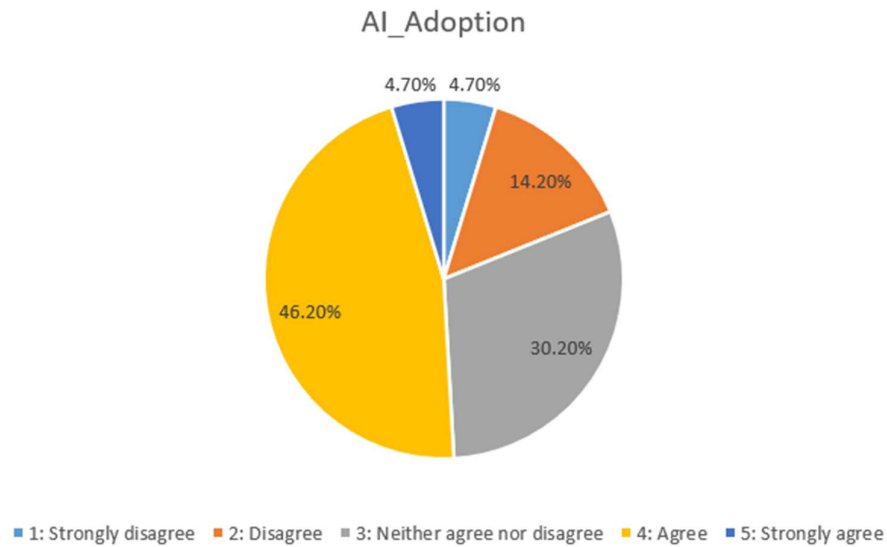


Figure 26: AI_Adoption Distribution.

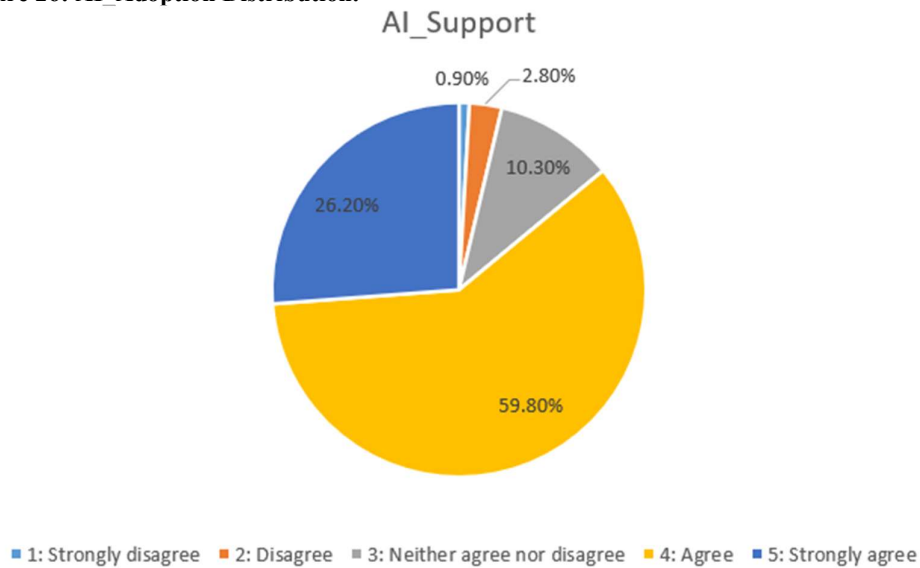


Figure 27: AI_Support Distribution.

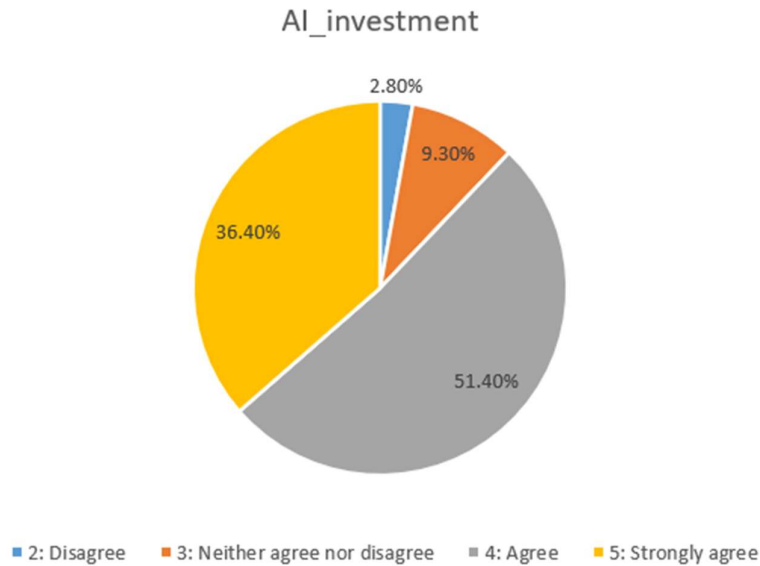


Figure 28: AI_investment Distribution.

Table 25: AI Adoption (Jasp Analysis)

Entire sample	AI_Support	AI_Investment	AI_Adoption
Valid	107	107	106
Missing	0	0	1
Mean	4.075	4.215	3.321
Std. Deviation	0.749	0.727	0.942

AI_Support: The average is 4.075 on a scale of 1 to 5. This suggests that participants believe managers' support is necessary for AI to be successfully adopted. The standard deviation is 0.749.

AI_Investment: The average is 4.215 on a scale of 1 to 5. This suggests that the participants anticipate their company will invest in AI within the next two years. The standard deviation is 0.727.

AI_Adoption: The average is 3.321 on a scale of 1 to 5. This suggests that the participants believe their company is ready to adopt AI, but further progress is needed. The standard deviation is 0.942, which demonstrates excellent variability.

Table 26: Motivation to use AI (Jasp Analysis)

Variable		Counts	Total	Proportion
AI_Motivation	Cost reduction	14	107	0.131
	Enhanced software quality	11	107	0.103
	Improved decision-making	5	107	0.047
	Increased productivity	77	107	0.720

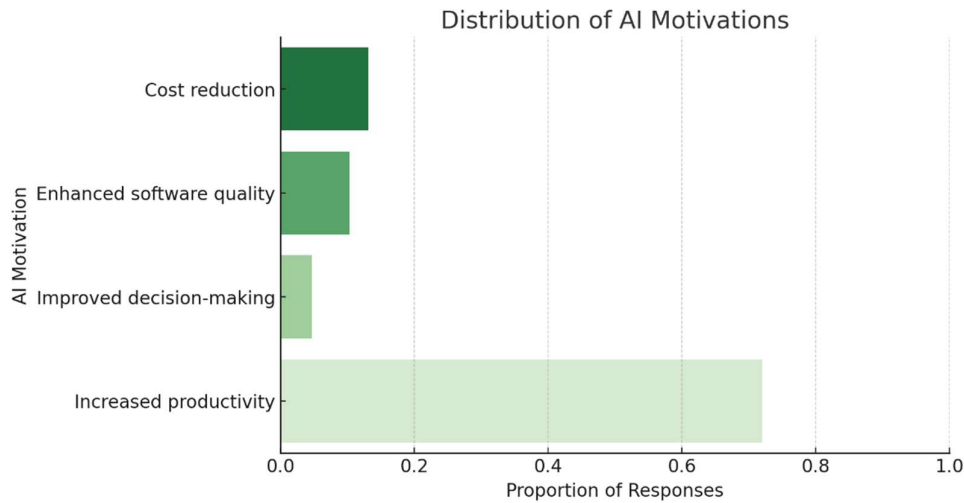


Figure 29: Distribution of AI Motivations

Most participants (72%) believe that the primary reason for using AI is increased productivity, whereas fewer than 5% think improved decision-making is a reason for its use. Approximately 10% believe that cost reduction and enhanced quality are reasons for incorporating AI into daily operations.

Table 27: Challenges of AI Usage (Jasp Analysis)

Variable		Counts	Total	Proportion
AI Challenges	All of the above, plus security concerns and a lack of quality in the analysis of complex scenarios.	1	107	0.009
	Data protection	1	107	0.009
	High costs	9	107	0.084
	Inconsistent results	41	107	0.383
	Limited understanding of AI	28	107	0.262
	N/A	1	107	0.009
	Not enough & mature tools	1	107	0.009
	Resistance to change	25	107	0.234

Concerning the AI adoption challenges, most participants (38.3%) still believe that AI presents a lack of consistency in the presented responses. A significant part of the participants also believe that they lack the proper knowledge to use AI or that companies face resistance to making the necessary changes to adopt AI (26.2% and 23.4%, respectively). Finally, some of the participants state that high costs could also be a barrier to adopting AI.

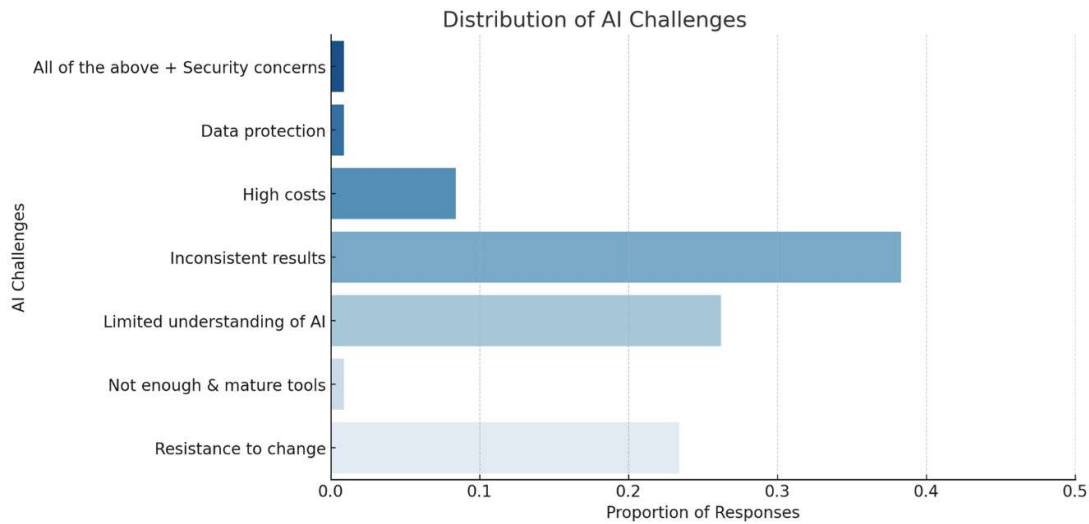


Figure 30: Distribution of AI Challenges

5.3 Correlations for examination of relationships

Following the initial analysis, a correlation analysis is necessary to determine whether a relationship exists between the different variables. Since the data are not normally distributed, Kendall's coefficient is used.

5.3.1 Experience

Table 28: Experience variable's correlation analysis (Jasp Analysis)

Variable	Experience	
1. Experience	Kendall's Tau B	—
	p-value	—
2. PM_Risks	Kendall's Tau B	-0.010
	p-value	0.912
3. AI_investment	Kendall's Tau B	-0.028
	p-value	0.748
4. AI_Support	Kendall's Tau B	0.076
	p-value	0.384
5. AI_Adoption	Kendall's Tau B	-0.216
	p-value	0.011
6. PM_Communication	Kendall's Tau B	-0.103
	p-value	0.231
7. PM_Schedules	Kendall's Tau B	-0.023
	p-value	0.793
8. PR_Frequency	Kendall's Tau B	-0.126
	p-value	0.131
9. HR_performance	Kendall's Tau B	-0.069
	p-value	0.418
10. HR_recruiting	Kendall's Tau B	-0.180
	p-value	0.037
11. HR_onboarding	Kendall's Tau B	-0.031
	p-value	0.723
12. QA_Reporting_quality	Kendall's Tau B	-0.028
	p-value	0.744
13. QA_Testing_Coverage	Kendall's Tau B	0.156

	p-value	0.073
14. QA_Testing_Speed	Kendall's Tau B	-0.099
	p-value	0.247
15. QA_Errors_reduce	Kendall's Tau B	-0.086
	p-value	0.315
16. PR_Innovation	Kendall's Tau B	-0.064
	p-value	0.456
17. PR_Time_improved	Kendall's Tau B	-0.233
	p-value	0.006
18. PR_Estimations	Kendall's Tau B	-0.298
	p-value	< .001
19. PR_Collaboration	Kendall's Tau B	-0.140
	p-value	0.105

Only the moderate and strong correlations will be mentioned:

PR_Estimations: Kendall's Tau B: -0.298, p-value: 0.001. A strong negative correlation with a statistically significant p-value ($p < 0.05$) indicates that more excellent experience is linked to a decreased perception of AI's effectiveness in task estimation.

PR_Time_improved: Kendall's Tau B: -0.233, p-value: 0.006. A strong negative correlation with a statistically significant p-value ($p < 0.05$) suggests that more excellent experience is associated with a diminished perception of AI's role in achieving tasks more quickly.

HR_recruiting: Kendall's Tau B: -0.180, p-value: 0.037. A strong negative correlation with statistical significance indicates that as experience increases, the perception that AI assists in the recruiting process tends to decrease.

AI_Adoption: Kendall's Tau B: -0.216, p-value: 0.011. A strong negative correlation with statistical significance ($p < 0.05$) suggests that increased experience is associated with the perception that companies are unprepared to adopt AI.

QA_Testing_Coverage: Kendall's Tau B: 0.156, p-value: 0.073. A weak correlation suggests that increased experience enhances the perception that AI aids with test coverage.

PR_Collaboration: Kendall's Tau B: -0.140; p-value: 0.105. There is a weak correlation indicating that an increase in experience leads to the assumption that AI does not aid team collaboration.

In conclusion, the experience level significantly impacts PR_Estimations, PR_Time_improved, AI_Adoption, and HR_recruiting variables.

5.3.2 Company Size

Table 29: Company size variable's correlation analysis (Jasp Analysis)

Variable	Company_size	
1. Company_size	Kendall's Tau B	—
	p-value	—
2. PR_Frequency	Kendall's Tau B	0.097

	p-value	0.240
3. PR_Time_improved	Kendall's Tau B	-0.013
	p-value	0.876
4. PR_Collaboration	Kendall's Tau B	-0.070
	p-value	0.420
5. PR_Estimations	Kendall's Tau B	-0.071
	p-value	0.408
6. PR_Innovation	Kendall's Tau B	0.140
	p-value	0.104
7. QA_Errors_reduce	Kendall's Tau B	0.134
	p-value	0.115
8. QA_Testing_Speed	Kendall's Tau B	-0.004
	p-value	0.965
9. QA_Testing_Coverage	Kendall's Tau B	0.049
	p-value	0.571
10. QA_Reporting_quality	Kendall's Tau B	0.048
	p-value	0.577
11. HR_recruiting	Kendall's Tau B	0.083
	p-value	0.337
12. HR_onboarding	Kendall's Tau B	-0.031
	p-value	0.716
13. HR_performance	Kendall's Tau B	0.032
	p-value	0.705
14. PM_Risks	Kendall's Tau B	0.017
	p-value	0.843
15. PM_Schedules	Kendall's Tau B	0.129
	p-value	0.139
16. PM_Communication	Kendall's Tau B	-0.135
	p-value	0.114
17. AI_Adoption	Kendall's Tau B	0.136
	p-value	0.109
18. AI_Support	Kendall's Tau B	0.192
	p-value	0.027
19. AI_investment	Kendall's Tau B	0.124
	p-value	0.155

AI_Support: Kendall's Tau B: 0.192, p-value: 0.027. A significant positive correlation with statistical significance ($p < 0.05$) suggests that as company size increases, the perception that management support is needed to adopt AI usage also increases. Overall, the analysis suggests that company size has a limited and weak association with most of the examined factors, except for the AI_Support variable.

5.3.3 Frequency

Table 30: Frequency variable's correlation analysis (Jasp Analysis)

Variable	PR_Frequency	
1. PR_Frequency	Kendall's Tau B	—
	p-value	—
2. PR_Time_improved	Kendall's Tau B	0.258
	p-value	0.002
3. PR_Collaboration	Kendall's Tau B	0.136
	p-value	0.104
4. AI_Support	Kendall's Tau B	0.076
	p-value	0.366
5. AI_investment	Kendall's Tau B	0.126

	p-value	0.137
6. PR_Innovation	Kendall's Tau B	0.188
	p-value	0.025
7. AI_Adoption	Kendall's Tau B	0.148
	p-value	0.074
8. PM_Communication	Kendall's Tau B	0.190
	p-value	0.023
9. PM_Schedules	Kendall's Tau B	0.033
	p-value	0.696
10. PM_Risks	Kendall's Tau B	0.042
	p-value	0.613
11. HR_performance	Kendall's Tau B	0.010
	p-value	0.904
12. HR_onboarding	Kendall's Tau B	-0.004
	p-value	0.960
13. HR_recruiting	Kendall's Tau B	0.147
	p-value	0.079
14. QA_Reporting_quality	Kendall's Tau B	0.090
	p-value	0.280
15. QA_Testing_Coverage	Kendall's Tau B	0.125
	p-value	0.138
16. QA_Testing_Speed	Kendall's Tau B	0.021
	p-value	0.802
17. PR_Estimations	Kendall's Tau B	0.057
	p-value	0.491
18. QA_Errors_reduce	Kendall's Tau B	-0.064
	p-value	0.439

PR_Time_improved: Kendall's Tau B: 0.258; p-value: 0.002. This indicates a statistically significant positive correlation ($p < 0.05$). It suggests that an increase in the usage of AI is associated with the perception that AI enhances the speed of task completion.

PM_Communication: Kendall's Tau B: 0.190; p-value: 0.023. A significant positive correlation with statistical significance suggests that more frequent AI usage is associated with a greater perception that AI facilitates better communication among stakeholders.

PR_Innovation: Kendall's Tau B: 0.188; p-value: 0.025. A significant positive correlation indicates that higher AI usage is associated with a greater perception that AI fosters innovation within companies.

AI_Adoption: Kendall's Tau B: 0.148; p-value: 0.074. A weak correlation suggests that higher AI usage is slightly linked to the perception that the company is prepared to adopt AI.

HR_recruiting: Kendall's Tau B: 0.147; p-value: 0.079. A weak correlation suggests that teams that utilize AI more frequently tend to experience slightly better outcomes in HR recruiting.

In conclusion, the frequency of AI usage appears to have a significant impact on the PR_Time_improved, PM_Communication, and PR_Innovation variables.

5.3.4 AI usage

Table 31: AI Adoption Variable's Correlation Analysis

Variable	AI_usage	
1. AI_usage	Kendall's Tau B	—
	p-value	—
2. PR_Frequency	Kendall's Tau B	-0.175
	p-value	0.047
3. PR_Time_improved	Kendall's Tau B	-0.162
	p-value	0.073
4. PR_Collaboration	Kendall's Tau B	-0.077
	p-value	0.403
5. PR_Estimations	Kendall's Tau B	-0.161
	p-value	0.076
6. PR_Innovation	Kendall's Tau B	-0.123
	p-value	0.179
7. QA_Errors_reduce	Kendall's Tau B	0.059
	p-value	0.520
8. QA_Testing_Speed	Kendall's Tau B	-0.086
	p-value	0.344
9. QA_Testing_Coverage	Kendall's Tau B	0.038
	p-value	0.681
10. QA_Reporting_quality	Kendall's Tau B	-0.083
	p-value	0.363
11. HR_recruiting	Kendall's Tau B	-0.076
	p-value	0.407
12. HR_onboarding	Kendall's Tau B	0.039
	p-value	0.675
13. HR_performance	Kendall's Tau B	-0.041
	p-value	0.652
14. PM_Risks	Kendall's Tau B	-0.065
	p-value	0.475
15. PM_Schedules	Kendall's Tau B	-0.053
	p-value	0.572
16. PM_Communication	Kendall's Tau B	-0.073
	p-value	0.424
17. AI_Adoption	Kendall's Tau B	-0.375
	p-value	< .001
18. AI_Support	Kendall's Tau B	-0.088
	p-value	0.345
19. AI_investment	Kendall's Tau B	-0.245
	p-value	0.008

AI_Adoption: Kendall's Tau B: -0.375. p-value: <0.001. There is a significant negative correlation that indicates participants who do not use AI tend to believe their organization is not ready to adopt AI.

AI_investment: Kendall's Tau B: -0.245. p-value: 0.008. There is a weak to moderate negative correlation, suggesting that participants who do not use AI believe their organization will not invest in AI.

PR_Frequency: Kendall's Tau B: -0.175. p-value: 0.047. There is a weak negative correlation between AI usage and PR frequency, indicating that individuals in organizations that have not adopted AI tend to use it infrequently.

PR_Time_improved: Kendall's Tau B: -0.162. p-value: 0.073. There is a weak negative correlation, indicating that people who do not use AI do not believe it helps with task completion time.

PR_Estimations: Kendall's Tau B: -0.161. p-value: 0.076. There is a weak negative correlation indicating that people who do not use AI do not believe it aids in task estimation. In conclusion, the use of AI appears to have a significant impact on the variables of AI Adoption and AI Investment.

5.4 ANOVA for group differences

The ANOVA test is used to analyze the differences between the groups of responders.

5.4.1 Impact of Experience in tasks in completion speed

*ANOVA -
PR_Time_improved*

Cases	Sum of Squares	df	Mean Square	F	p
Experience	8.573	3	2.858	3.339	0.025
Residuals	49.636	58	0.856		

*Descriptives -
PR_Time_improved*

Experience	N	Mean	SD	SE	Coefficient of variation
Less than 1 year	2	5.000	0.000	0.000	0.000
1-5 years	11	4.273	0.467	0.141	0.109
6-9 years	27	4.000	0.784	0.151	0.196
More than 10 years	22	3.455	1.224	0.261	0.354

The F-value (3.339) indicates that the variability between experience groups is more significant than anticipated under the null hypothesis (which assumes no differences among groups). The p-value is statistically significant at 0.05, allowing us to reject the null hypothesis. This indicates a significant difference in PR_Time_improved across various experience levels. The mean PR_Time_improved declines as the experience level rises.

Additionally, the standard deviation increases with experience level, suggesting more significant variability in PR_Time_improved among more experienced individuals.

5.4.2 Influence of Job Role on Frequency Usage

*ANOVA -
PR Frequency*

Cases	Sum of Squares	df	Mean Square	F	p
Role	6.511	4	1.628	1.236	0.300
Residuals	134.274	102	1.316		

*Descriptives -
PR Frequency*

Role	N	Mean	SD	SE	Coefficient of variation
Engineer	62	3.790	0.871	0.111	0.230
HR Professional	8	3.000	1.512	0.535	0.504
Manager	5	3.200	1.304	0.583	0.407
Project Manager	20	3.450	1.538	0.344	0.446
Quality Assurance Specialist	12	3.750	1.357	0.392	0.362

We observe that the p-value is greater than 0.05, indicating there is no statistically significant difference in PR_Frequency among different job roles. The F-statistic is relatively low, indicating that the variance between groups is slight compared to the variance within groups.

Engineers (3.79) and QA Specialists (3.75) use AI more frequently than other roles with HR professionals having the lowest score.

5.4.3 Influence of Company Size on Frequency Usage

*ANOVA -
PR Frequency*

Cases	Sum of Squares	df	Mean Square	F	p
Company_size	2.837	3	0.946	0.706	0.551
Residuals	137.948	103	1.339		

*Descriptives -
PR Frequency*

Company_size	N	Mean	SD	SE	Coefficient of variation
Fewer than 50	5	3.400	1.517	0.678	0.446
50-200	28	3.393	1.066	0.201	0.314
201-500	23	3.783	1.313	0.274	0.347
More than 500	51	3.725	1.097	0.154	0.294

We fail to reject the null hypothesis since $p = 0.551 (> 0.05)$. This means there is no significant difference in usage frequency across different company sizes.

5.4.4 Influence of Company Size on AI Adoption

ANOVA - AI usage

Cases	Sum of Squares	df	Mean Square	F	p
Company_size	2.837	3	0.742	3.864	0.012
Residuals	137.948	103	0.192		

Descriptives - AI usage

Company_size	N	Mean	SD	SE	Coefficient of variation
Fewer than 50	5	1.400	0.548	0.245	0.391
50-200	28	1.321	0.476	0.090	0.360
201-500	23	1.522	0.511	0.106	0.336
More than 500	51	1.157	0.367	0.051	0.317

The p-value for company size is 0.012, which is statistically significant at the conventional 0.05 level. A value of 3.864 suggests a moderate difference in AI adoption between company sizes.

The highest AI adoption is in companies with 201-500 employees (Mean = 1.522), and the lowest is in companies with more than 500 employees. Small companies (Fewer than 50) and medium-sized companies (50-200) show moderate adoption (Mean = 1.400 and 1.321, respectively).

5.4.5 Influence of Experience on AI's Efficiency in Bug Resolution

ANOVA - QA Errors reduce

Cases	Sum of Squares	df	Mean Square	F	p
Experience	3.045	3	1.015	1.332	0.268
Residuals	78.507	103	0.762		

Descriptives - QA Errors reduce

Experience	N	Mean	SD	SE	Coefficient of variation
Less than 1 year	3	3.667	0.577	0.333	0.157
1-5 years	23	3.609	0.783	0.163	0.217
6-9 years	38	3.184	0.865	0.140	0.272
More than 10 years	43	3.279	0.934	0.142	0.285

Since the p-value (0.268) is greater than 0.05, there is no statistically significant effect of experience on the perception that AI efficiently identifies Critical bugs. The means are relatively close across experience levels. Standard deviations suggest some variation, but there is no clear trend. The coefficient of variation increases with experience, indicating higher relative dispersion in more experienced groups.

5.4.6 Influence of Experience on AI's Efficiency in Effort Estimation

*ANOVA -
PR Estimations*

Cases	Sum of Squares	df	Mean Square	F	p
Experience	9.452	3	3.151	4.977	0.003
Residuals	65.202	103	0.633		

*Descriptives -
PR Estimations*

Experience	N	Mean	SD	SE	Coefficient of variation
Less than 1 year	3	3.667	1.155	0.667	0.315
1-5 years	23	3.609	0.656	0.137	0.182
6-9 years	38	3.053	0.733	0.119	0.240
More than 10 years	43	2.860	0.889	0.136	0.311

The p-value (0.003) is less than 0.05, indicating a statistically significant effect of experience on the perception of AI efficiency in effort estimation. The mean value of PR_Estimation scores decreases as experience increases (from 3.667 in group 1 to 2.860 in group 4). Standard deviation (SD) is higher for groups with lower and higher experience (Groups 1 & 4), indicating more significant variability in PR_Estimation.

5.4.7 Influence of Experience on AI's Frequency Usage

*ANOVA -
PR Frequency*

Cases	Sum of Squares	df	Mean Square	F	p
Experience	7.511	3	2.504	1.935	0.129
Residuals	133.274	103	1.294		

*Descriptives -
PR Estimations*

Experience	N	Mean	SD	SE	Coefficient of variation
Less than 1 year	3	2.667	1.528	0.882	0.573
1-5 years	23	3.913	1.125	0.235	0.287
6-9 years	38	3.789	1.069	0.173	0.282
More than 10 years	43	3.419	1.180	0.180	0.345

The experience does not affect the frequency of usage. The p-value of 0.129 indicates that the differences among groups are not statistically significant at the conventional 0.05 level.

6. Discussion of the Results

6.1 Summary of Key Findings

Descriptive statistics: Most of the participants hold the position of Engineer, which is typical for Software Development companies. Furthermore, the survey targeted medium to senior profiles (more than 70% of the participants had more than 6 years of experience), as these profiles tend to have a more complete view of AI's performance perspective. Around half of the participants work for large companies (47.7%), and 70% declared that their company has adopted AI. Finally, although more than half of the participants use AI several times a week or even daily (~60%), the remaining 40% only use AI occasionally per month.

General conclusions:

- In the project management domain, most participants, including many project management professionals, believe that AI positively impacts schedule drafting, with a mean of 3.4. Nevertheless, its ability to identify risks and facilitate communication is somewhat limited. Regarding AI usage among PM professionals, only 50% of them utilize AI on a weekly basis.
- In the human resource domain, most participants do not feel that AI significantly contributes to human resource processes. Many HR professionals use AI occasionally each week but not daily. Most of them perceive that AI has a slight impact on employee performance evaluations (mean score of 3.25).
- Regarding productivity variables, most participants believe that AI enhances innovation and task speed, whereas its effectiveness in team collaboration and work estimation is lacking. Among engineers, 63% use AI weekly and agree that it contributes to innovation and task completion.
- Regarding quality assurance variables, most participants recognize the added value of AI's contribution to quality assurance, particularly in test coverage. However, quality assurance professionals hold a slightly different perspective from the general population, believing that AI primarily benefits testing coverage rather than other areas of application. More than 70% of them use AI several times per week.
- Regarding managers (directors, C-level executives, etc.), they believe that AI benefits all project management variables, especially in HR performance evaluation

within HR practices, innovation, task completion within productivity variables, and all quality assurance areas.

Correlations and respondent characteristics:

- Regarding the experience, the analysis revealed that as participants' experience increased, their perception of AI's contribution to estimation, the recruiting process, and time efficiency in task completion decreased.
- Regarding company size, the analysis indicated a positive correlation between company size and the belief that management support is necessary for AI adoption. Conversely, company size did not directly influence other performance variables.
- Concerning AI usage frequency, more frequent use of AI led to a more excellent perception of its benefits in communication, innovation, and faster task completion. Additionally, the findings show a weak positive correlation between AI adoption and recruiting.
- The impact of AI usage among professionals shapes the belief that companies are prepared to invest in and readopt AI, influencing the frequency of AI usage.
- Participants who do not use AI believe their organization is unprepared to adopt it and doubt that there will be investment in AI in the next two years. They do not share the belief that AI positively contributes to the accuracy and speed of task completion.

AI challenges and future improvements:

Participants indicated that adopting and using AI is challenging. 38.3% believe AI produces inconsistent outputs, 26% feel they lack the proper knowledge to utilize AI effectively, and another 23% expressed concerns that adopting AI would necessitate changes that many people are reluctant to make. Security concerns were also mentioned.

Moreover, most participants (72%) believe the primary reason for using AI is to enhance productivity, while the remainder think AI can help reduce costs (10%) and improve quality (10%).

7. Conclusion

7.1 Conclusion of the Results

The results of our hypothesis are presented below:

Hypothesis 1: How does AI impact the productivity of software development teams?

Expected Result: A high score is expected, with a higher score among junior professionals.

Actual Results: There is a direct relation between seniority and the perception of productivity. Junior profiles increasingly rely on AI for task completion.

Justification: Survey data indicates a correlation between experience level and AI usage. Junior professionals with less experience report a higher reliance on AI for task completion, aligning with the "Actual Result" of increased reliance among junior profiles.

Hypothesis 2: What role does AI play in improving the Quality (software testing phase)?

Expected Result: A high score is expected among Software Development company professionals.

Actual Results: Although, in general, participants believe that AI helps with quality assurance, QA professionals seem to expect more improvements, and they do not believe that AI helps in critical bug identification or regression speed improvement.

Justification: Although QA professionals generally hold a favorable perspective, they express specific concerns about AI's limitations, particularly in identifying critical bugs and its speed in regression testing, which aligns closely with the "Actual Result." More than 70% of QA professionals who utilize AI several times a week believe they are adequately equipped to evaluate AI's influence on QA. However, they do not currently engage with AI on a daily basis; instead, they use it several times each week.

Hypothesis 3: How does AI influence HR practices in software companies?

Expected Result: A medium score is expected, taking into consideration the medium adoption of usage in the HR industry.

Actual Results: The survey reveals that participants struggle to articulate a definitive opinion on the impact of AI on HR processes. Additionally, it highlights that merely 50% of HR professionals utilize AI tools on a regular basis.

Justification: The "Actual Result" of unclear impact and limited usage is directly supported by survey data, which show a lack of consensus on AI's HR benefits and only 50% frequent

use among HR professionals. This limited and ambiguous usage corresponds with the difficulty participants had in expressing a clear view.

Hypothesis 4: To what extent does AI enhance project management practices?

Expected Result: A medium score is expected, considering the medium adoption of AI in the day-to-day activities of PM professionals.

Actual Results: According to the survey, only 50% of project management professionals frequently use AI. They believe that artificial intelligence aids in risk identification and schedule drafting; however, it has not yet provided assistance to the stakeholders' management.

Justification: The "Actual Result" of limited AI usage among PM professionals (50%) directly supports the claim of moderate adoption. The survey's findings highlight AI's role in identifying risks and drafting schedules, confirming the assessments of professionals.

Hypothesis 5: How could AI be better adopted by software development companies?

Expected Result: Companies are not mature enough to fully exploit AI capabilities.

Actual Results: According to the survey, only 70% of companies have adopted AI. Most barriers include high costs, insufficient training and knowledge, and a lack of willingness to change operational procedures. However, although most participants do not think their company is willing to adopt AI, they expect their company to invest in AI usage in the next two years.

Justification: The limited adoption rate of 70%, along with the identified barriers such as high costs, inadequate training, and resistance to change, directly supports the assumptions found in the literature. While AI presents significant potential, many challenges remain for professionals trying to maximize its use.

The integration of artificial intelligence (AI) in software development companies has reached a notable milestone, with nearly all professionals, regardless of their experience, incorporating it into their routines. However, our research uncovers a complex picture of AI usage and perceived advantages. A distinct trend reveals that junior professionals rely heavily on AI to speed up task completion, whereas senior professionals are less convinced of its substantial impact on their productivity. This difference highlights the importance of

tailoring AI training and integration methods to meet the distinct needs and expectations of individuals at various seniority levels.

Our research indicates varying levels of AI effectiveness across different sectors. While AI shows promise in risk identification and schedule drafting within project management, as well as offering general support in quality assurance, its utilization and perceived benefits are significantly lower in HR processes. This implies that AI technologies have not yet been fully adopted to address the complex needs of these areas. QA professionals raise concerns about AI's capability to detect critical bugs and enhance regression testing speed, while HR professionals find it challenging to define tangible advantages. This highlights a disparity between AI's current abilities and the expectations of specialists in these particular domains.

Despite these hurdles, companies are expected to significantly increase their AI investments over the next two years. Nonetheless, challenges such as high costs, inadequate training, and reluctance to adopt change need to be addressed to unlock the full potential of AI. To successfully integrate AI, businesses should create strategic plans that align AI capabilities with specific business needs, invest in thorough employee training to enhance comprehension and application, and incorporate AI into key decision-making processes. By overcoming these obstacles and emphasizing strategic integration, software development firms can enhance the impact of AI and harness its benefits to foster innovation and efficiency.

7.1.1 How Software Development Companies Can Adopt AI

According to the survey, many professionals emphasized the lack of knowledge regarding the use of AI. Software development companies should organize boot camps or training sessions on the possibilities and capabilities that AI can bring to daily work, as well as how to best utilize it in various circumstances. Additionally, a knowledge-sharing mentality is crucial for professionals to exchange their experiences. Another proposal would be to launch hands-on pilot projects, allowing professionals to experiment with AI on a limited scale before further adopting it. Managers should facilitate the implementation of necessary operational changes so that companies and employees can adopt AI tools smoothly. The best practice is to start with small projects and scale up while integrating AI into existing workflows. Managers should also be proactive and integrate operational changes into the

change management process, while maintaining clear communication plans. While operational costs are high, there is an expectation that most companies will invest more in AI technology, considering that, according to the survey, AI is viewed as a valuable tool for increasing productivity. Companies should use cost-effective infrastructure, such as cloud-based, where the companies pay as they use. At the same time, it is essential to conduct a cost-benefit analysis that considers all expenses, such as training, maintenance, and the AI license or development costs. AI projects should be treated in an Agile mindset, meaning their performance should continuously be monitored. Simultaneously, the use of AI requires adherence to the best security standards and compliance with GDPR legislation. Companies should employ best security practices from the beginning of the project, ensuring data privacy protection. Choosing trusted AI partners that adhere to the same practices is also important. It is evident that while AI has begun to be used and professionals clearly see benefits from its use, some distance remains before AI is regarded as a game changer in terms of performance. The human factor, effective project management, good human resource practices, and clear organization still play a crucial role in organizational performance. Companies should consider AI a tool to complement the teams, not replace them. Project managers should understand that, although AI can assist with planning, scheduling, and estimation, they ultimately control the project and utilize the enhanced capabilities that AI offers to succeed. Finally, it is suggested that companies that want to adopt AI should establish clear performance metrics to understand AI's role in performance improvement.

7.2 Limitations of Work

The research survey and methodology have certain limitations that were discussed previously. In summary, the sample size may not represent the entire software development industry, and self-reported data from participants could introduce biases or inaccuracies. The cross-sectional design aims to capture the opinions of various roles within software development companies. As a result, it provides a snapshot of experiences, and some conflicting factors may have been overlooked. Nonetheless, this study offers valuable insights into the impact of AI on performance in various areas of software development that influence performance, including human resources, quality assurance, and project management.

7.3 Suggestions for future research

Building on these identified research directions, future studies can explore several promising fields:

- **Integrating AI in HR Practices:** Future studies should investigate how AI can further improve talent acquisition, performance evaluation, and employee engagement in software development firms. Metrics should be applied to try and quantify the benefits and challenges of AI-driven methods compared to traditional human resource practices.
- **Emerging Role in Project Management:** Research into AI's potential to optimize resource allocation, risk management, and timeline forecasting in project management is needed. Studies could examine the integration of AI within agile project methodologies and assess its impact on decision-making in agile software development methodology and other software development models.
- **Data Privacy, Security, and Ethics:** With the increasing usage of AI-driven language models, it is crucial to address data privacy and security issues. Future research could develop and validate the ethical use of AI while protecting sensitive data. A combination of technical and legal studies may be a more effective approach for this type of research.
- **Enhancing Collaboration and Communication:** Further investigations should examine how AI can foster collaboration among team members and stakeholders. Studies may evaluate the effects of AI tools on team dynamics, communication effectiveness, and overall project outcomes, particularly in remote or hybrid settings. Researching AI integration in collaborative platforms could uncover strategies for bridging communication gaps and creating a more cohesive work environment.

In conclusion, pursuing these research pathways will deepen our understanding of AI's role in enhancing organizational performance and provide practical guidance for its responsible and effective application. This holistic approach will ultimately enable organizations to leverage AI to enhance operational efficiency while addressing key ethical and security challenges.

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Appendix A: Survey design and results

Demographics related questions:

What is your role in your organization?

- ☐ Software Developer
- ☐ Project Manager
- ☐ Quality Assurance Specialist
- ☐ HR Professional
- ☐ Business Analyst
- ☐ DevOps Engineer
- ☐ Other: _____

How many years of experience do you have in the software development industry?

- ☐ Less than 1 year
- ☐ 1–5 years
- ☐ 6–9 years
- ☐ More than 10 years

How many employees does your company have?

- ☐ Fewer than 50
- ☐ 50–200
- ☐ 201–500
- ☐ More than 500

Does your organization currently use AI tools in its operations?

- ☐ Yes
- ☐ No

Productivity related to performance questions:

How frequently do you use AI tools in your day-to-day work?

- ☐ Not at all
- ☐ Rarely (1 -2 times per month)
- ☐ Occasionally (Several times per month)
- ☐ Regularly (3- 4 times per week)
- ☐ Always (every day)

From 1 to 5 (1 = Strongly disagree, 5 = Strongly agree), do you agree that AI has reduced the time required for code generation, code completion and code proposals?

- ☐ 1: Strongly disagree
- ☐ 2: Disagree
- ☐ 3: Neither agree nor disagree
- ☐ 4: Agree
- ☐ 5: Strongly agree

From 1 to 5 (1 = Strongly disagree, 5 = Strongly agree), do you agree that AI has improved team collaboration?

- ☐ 1: Strongly disagree
- ☐ 2: Disagree
- ☐ 3: Neither agree nor disagree
- ☐ 4: Agree
- ☐ 5: Strongly agree

From 1 to 5 (1 = Strongly disagree, 5 = Strongly agree), do you agree that AI has improved the accuracy of task estimations in your team?

- ☐ 1: Strongly disagree
- ☐ 2: Disagree
- ☐ 3: Neither agree nor disagree
- ☐ 4: Agree
- ☐ 5: Strongly agree

What is the most significant area of software development that AI could improve?

- ☐ Requirements gathering
- ☐ Coding
- ☐ Testing
- ☐ Deployment
- ☐ Planning
- ☐ Documentation
- ☐ Other: _____

From 1 to 5 (1 = Strongly disagree, 5 = Strongly agree), do you agree that AI supports innovation in software development industry?

- ☐ 1: Strongly disagree
- ☐ 2: Disagree
- ☐ 3: Neither agree nor disagree
- ☐ 4: Agree
- ☐ 5: Strongly agree

Quality related to performance questions:

From 1 to 5 (1 = Strongly disagree, 5 = Strongly agree), do you agree that AI impacts the speed of regression testing in your projects?

- ☐ 1: Strongly disagree
- ☐ 2: Disagree
- ☐ 3: Neither agree nor disagree
- ☐ 4: Agree
- ☐ 5: Strongly agree

From 1 to 5 (1 = Strongly disagree, 5 = Strongly agree), do you agree that AI impacts the speed of regression testing in your projects?

- ☐ 1: Strongly disagree
- ☐ 2: Disagree
- ☐ 3: Neither agree nor disagree
- ☐ 4: Agree
- ☐ 5: Strongly agree

From 1 to 5 (1 = Strongly disagree, 5 = Strongly agree), does the use of AI in software testing improve test coverage?

- ☐ 1: Strongly disagree
- ☐ 2: Disagree
- ☐ 3: Neither agree nor disagree
- ☐ 4: Agree
- ☐ 5: Strongly agree

From 1 to 5 (1 = Strongly disagree, 5 = Strongly agree) do you agree that AI-generated quality reports are better than manual-generated ones?

- ☐ 1: Strongly disagree
- ☐ 2: Disagree
- ☐ 3: Neither agree nor disagree
- ☐ 4: Agree
- ☐ 5: Strongly agree

HR processes related to performance questions:

From 1 to 5 (1 = Strongly disagree, 5 = Strongly agree), do you agree that AI has supported your organization's recruitment processes (reducing bias, screening cv, etc)?

- ☐ 1: Strongly disagree
- ☐ 2: Disagree
- ☐ 3: Neither agree nor disagree
- ☐ 4: Agree
- ☐ 5: Strongly agree

From 1 to 5 (1 = Strongly disagree, 5 = Strongly agree), do you agree that AI has impacted the onboarding processes in your organization?

- ☐ 1: Strongly disagree
- ☐ 2: Disagree
- ☐ 3: Neither agree nor disagree
- ☐ 4: Agree
- ☐ 5: Strongly agree

From 1 to 5 (1 = Strongly disagree, 5 = Strongly agree), do agree that AI contributes to monitoring and improving employee performance metrics?

- ☐ 1: Strongly disagree
- ☐ 2: Disagree
- ☐ 3: Neither agree nor disagree
- ☐ 4: Agree
- ☐ 5: Strongly agree

Project Management related to performance questions:

From 1 to 5 (1 = Strongly disagree, 5 = Strongly agree), do you agree that AI has helped identify project risks?

- ☐ 1: Strongly disagree
- ☐ 2: Disagree
- ☐ 3: Neither agree nor disagree
- ☐ 4: Agree
- ☐ 5: Strongly agree

From 1 to 5 (1 = Strongly disagree, 5 = Strongly agree), do you agree that AI facilitates the generation of project timelines and schedules?

- ☐ 1: Strongly disagree
- ☐ 2: Disagree
- ☐ 3: Neither agree nor disagree
- ☐ 4: Agree
- ☐ 5: Strongly agree

From 1 to 5 (1 = Strongly disagree, 5 = Strongly agree), do you agree that AI has facilitated communication between project stakeholders?

- ☐ 1: Strongly disagree
- ☐ 2: Disagree
- ☐ 3: Neither agree nor disagree
- ☐ 4: Agree
- ☐ 5: Strongly agree

AI Adoption related questions:

What are the primary challenges in integrating AI into the software development lifecycle?

- ☐ High costs
- ☐ Limited understanding of AI
- ☐ Resistance to change
- ☐ Inconsistent results
- ☐ Other: _____

What are the main motivations for adopting AI in your organization?

- ☐ Increased productivity
- ☐ Enhanced software quality
- ☐ Cost reduction
- ☐ Improved decision-making

From 1 to 5 (1 = Strongly disagree, 5 = Strongly agree), do you agree that your organization is ready to adopt AI?

- ☐ 1: Strongly disagree
- ☐ 2: Disagree
- ☐ 3: Neither agree nor disagree
- ☐ 4: Agree
- ☐ 5: Strongly agree

From 1 to 5 (1 = Strongly disagree, 5 = Strongly agree) do you agree that top management's support is important for successful AI adoption?

- ☐ 1: Strongly disagree
- ☐ 2: Disagree
- ☐ 3: Neither agree nor disagree
- ☐ 4: Agree
- ☐ 5: Strongly agree

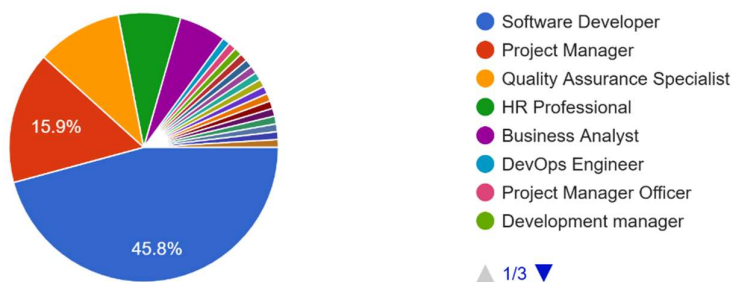
From 1 to 5 (1 = Strongly disagree, 5 = Strongly agree) do you agree that your organization will increase its investment in AI in the next two years?

- ☐ 1: Strongly disagree
- ☐ 2: Disagree
- ☐ 3: Neither agree nor disagree
- ☐ 4: Agree
- ☐ 5: Strongly agree

Survey Results:

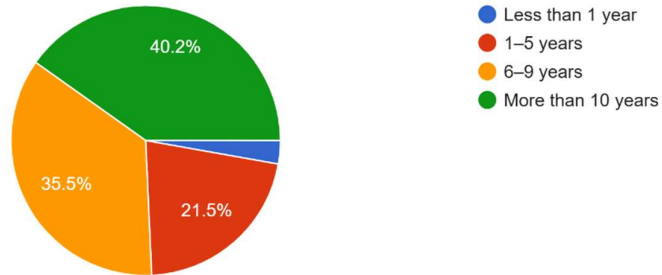
What is your role in your organization?

107 responses



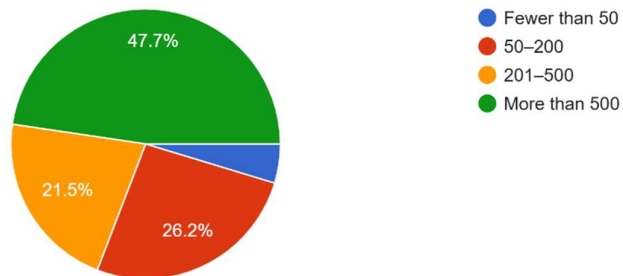
How many years of experience do you have in the software development industry?

107 responses



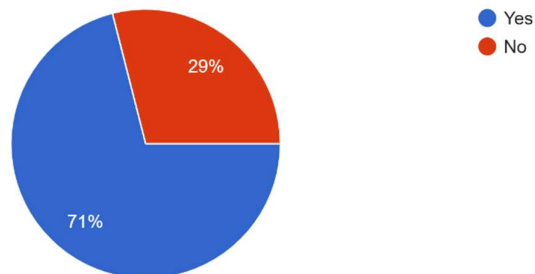
How many employees does your company have?

107 responses



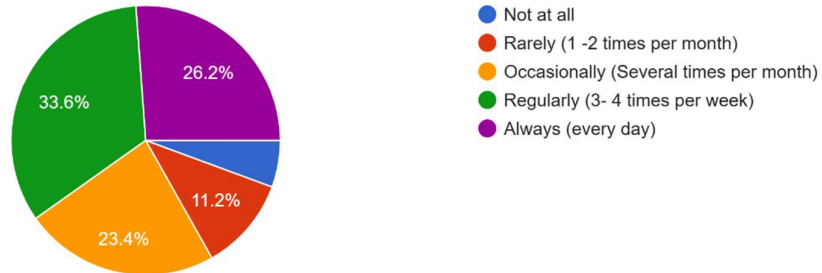
Does your organization currently use AI tools in its operations?

107 responses



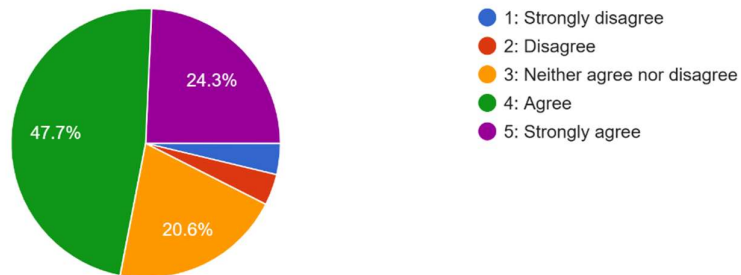
How frequently do you use AI tools in your day-to-day work?

107 responses



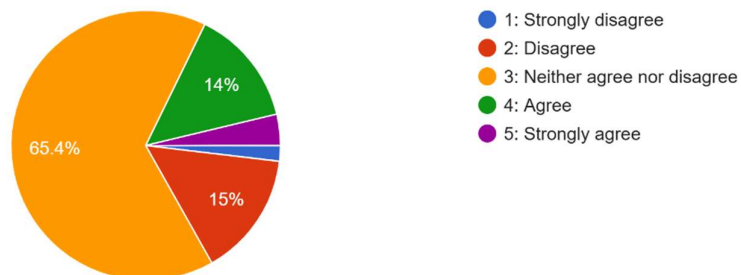
From 1 to 5 (1 = Strongly disagree, 5 = Strongly agree), do you agree that AI has reduced the time required for code generation, code completion and code proposals?

107 responses



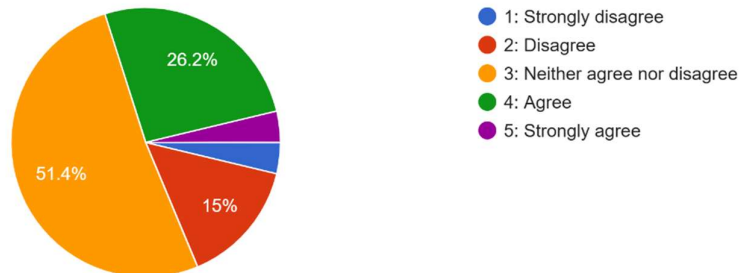
From 1 to 5 (1 = Strongly disagree, 5 = Strongly agree), do you agree that AI has improved team collaboration?

107 responses



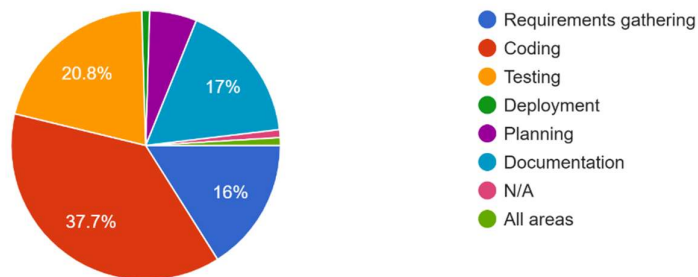
From 1 to 5 (1 = Strongly disagree, 5 = Strongly agree), do you agree that AI has improved the accuracy of task estimations in your team?

107 responses



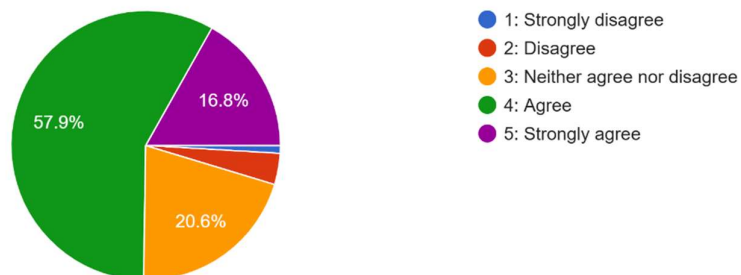
What is the most significant area of software development that AI could improve?

106 responses



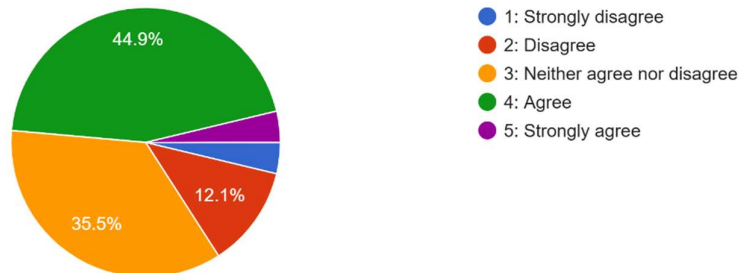
From 1 to 5 (1 = Strongly disagree, 5 = Strongly agree), do you agree that AI supports innovation in software development industry?

107 responses



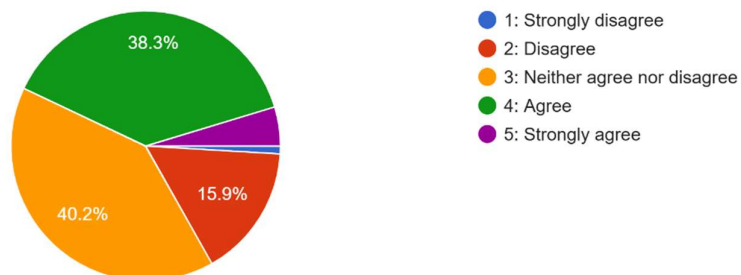
From 1 to 5 (1 = Strongly disagree, 5 = Strongly agree), do you agree that AI is efficient in identifying critical bugs during testing?

107 responses



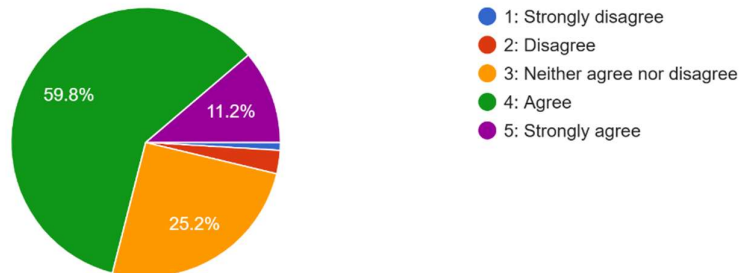
From 1 to 5 (1 = Strongly disagree, 5 = Strongly agree), do you agree that AI impacts the speed of regression testing in your projects?

107 responses



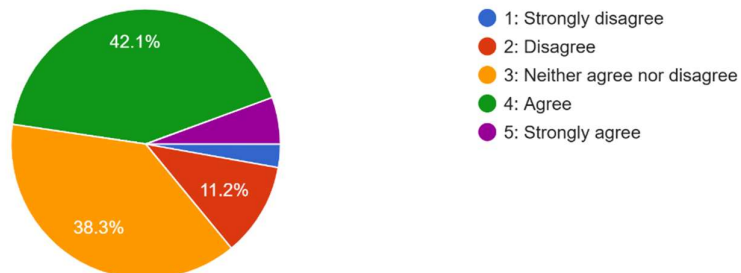
From 1 to 5 (1 = Strongly disagree, 5 = Strongly agree), does the use of AI in software testing improve test coverage?

107 responses



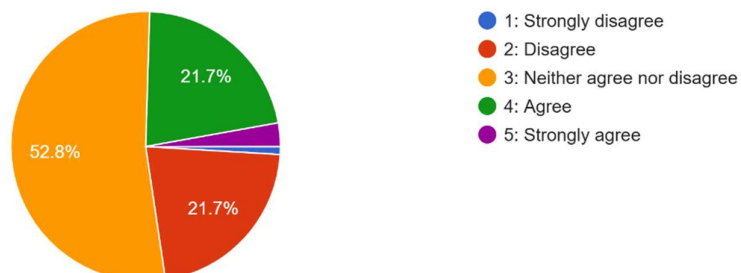
From 1 to 5 (1 = Strongly disagree, 5 = Strongly agree) do you agree that AI-generated quality reports are better than manual-generated ones?

107 responses



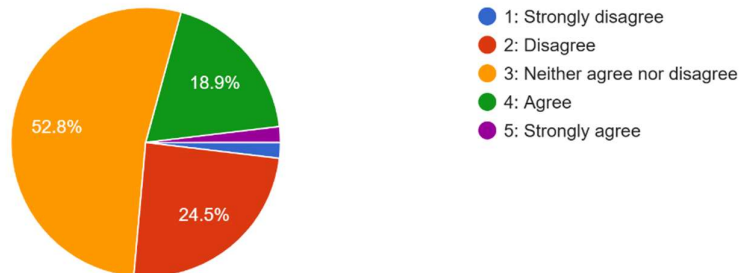
From 1 to 5 (1 = Strongly disagree, 5 = Strongly agree), do you agree that AI has supported your organization's recruitment processes (reducing bias, screening cv, etc)?

106 responses



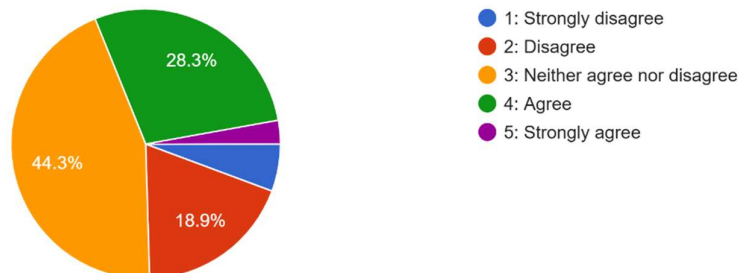
From 1 to 5 (1 = Strongly disagree, 5 = Strongly agree), do you agree that AI has impacted the onboarding processes in your organization?

106 responses



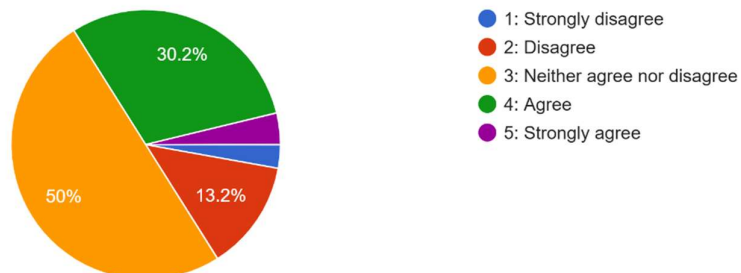
From 1 to 5 (1 = Strongly disagree, 5 = Strongly agree), do agree that AI contributes to monitoring and improving employee performance metrics?

106 responses



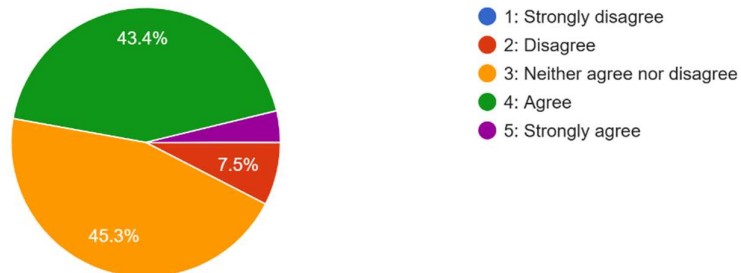
From 1 to 5 (1 = Strongly disagree, 5 = Strongly agree), do you agree that AI has helped identify project risks?

106 responses



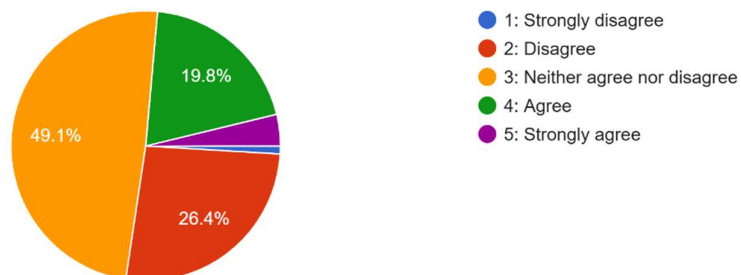
From 1 to 5 (1 = Strongly disagree, 5 = Strongly agree), do you agree that AI facilitates the generation of project timelines and schedules?

106 responses



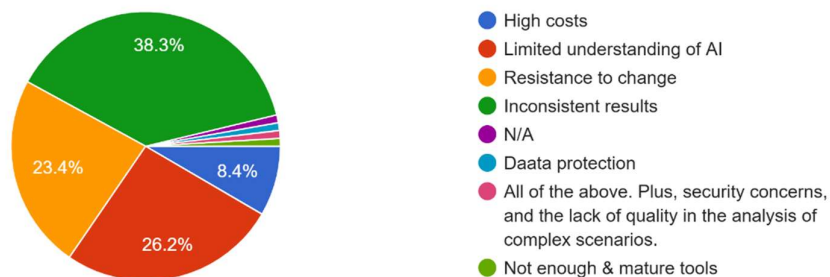
From 1 to 5 (1 = Strongly disagree, 5 = Strongly agree), do you agree that AI has facilitated communication between project stakeholders?

106 responses



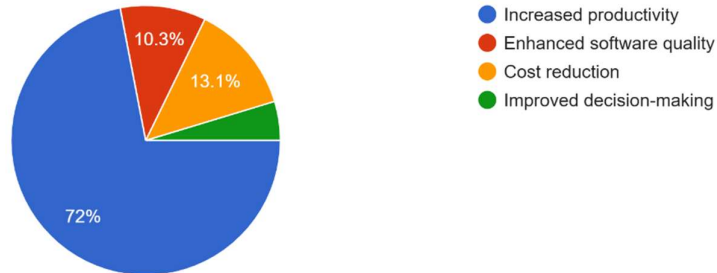
What are the primary challenges in integrating AI into the software development lifecycle?

107 responses



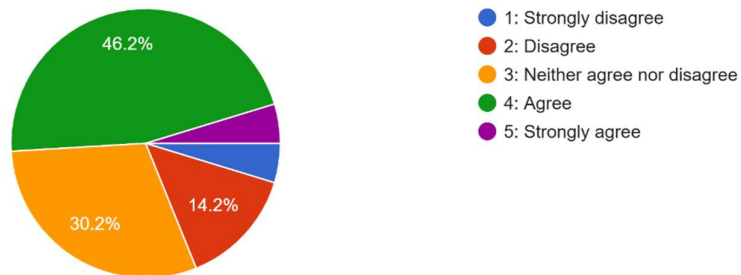
What are the main motivations for adopting AI in your organization?

107 responses



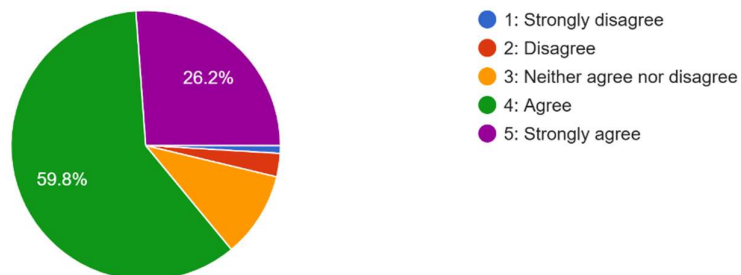
From 1 to 5 (1 = Strongly disagree, 5 = Strongly agree), do you agree that your organization is ready to adopt AI?

106 responses



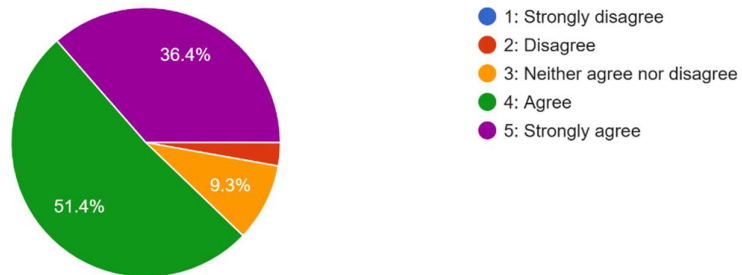
From 1 to 5 (1 = Strongly disagree, 5 = Strongly agree) do you agree that top management's support is important for successful AI adoption?

107 responses



From 1 to 5 (1 = Strongly disagree, 5 = Strongly agree) do you agree that your organization will increase its investment in AI in the next two years?

107 responses



Appendix B: Description of variables

Concerning the role in the organization, the initial responses were grouped into five major categories: Project Manager, Engineer, HR Professional, Manager, and Quality Assurance Specialist, according to the following table:

Role	Role Grouping
Project Manager	Project Manager
Software Developer	Engineer
Business Analyst	Engineer
HR Professional	HR Professional
Manager	Manager
Quality Assurance Specialist	Quality Assurance Specialist
Engineering director	Manager
Data Solutions Architect	Engineer
Data Engineer	Engineer
Head of Data Delivery Management	Manager
IT team leader	Project Manager
Solutions Architect	Engineer
Software architect	Engineer
DevOps Engineer	Engineer
Project Manager Officer	Project Manager
PMO	Project Manager
Development Manager	Manager
Data Architect	Engineer
Product Owner	Manager
Solution Architect	Engineer
Test Manager	Quality Assurance Specialist

Table 32: Role mappings

Variable	Description	Comments
Role	What is your role in your organization?	Project Manager, Engineer, HR Professional, Manager, and Quality Assurance Specialist
Experience	Years of experience	1: less than a year

		2: 1-5 years 3: 6-9 years 4: more than 10 years
Company_size	Company size (very roughly, employees)	1: Fewer than 50 2: 50-200 3: 201-500 4: more than 500
AI_usage	Does the organization currently use AI tools in its operations	1: yes 2: no
PR_Frequency	How frequently is AI used in the day-to-day work	1: Not at all 2: Rarely (1 -2 times per month) 3: Occasionally (Several times per month) 4: Regularly (3- 4 times per week) 5: Always (every day)
PR_Time_improved	From 1 to 5 (1 = Strongly disagree, 5 = Strongly agree), do you agree that AI has reduced the time required for code generation, code completion and code proposals?	1 = Strongly disagree, 5 = Strongly agree
PR_Collaboration	From 1 to 5 (1 = Strongly disagree, 5 = Strongly agree), do you agree that AI has improved team collaboration?	1 = Strongly disagree, 5 = Strongly agree
PR_Estimations	From 1 to 5 (1 = Strongly disagree, 5 = Strongly agree), do you agree that AI has improved the accuracy of task estimations in your team?	1 = Strongly disagree, 5 = Strongly agree
PR_Improvement	What is the most significant area of software development that AI could improve?	
PR_Innovation	From 1 to 5 (1 = Strongly disagree, 5 = Strongly agree), do you agree that AI supports innovation in software development industry?	1 = Strongly disagree, 5 = Strongly agree

QA_Errors_reduce	From 1 to 5 (1 = Strongly disagree, 5 = Strongly agree), do you agree that AI is efficient in identifying critical bugs during testing?	1 = Strongly disagree, 5 = Strongly agree
QA_Testing_Speed	From 1 to 5 (1 = Strongly disagree, 5 = Strongly agree), do you agree that AI impacts the speed of regression testing in your projects?	1 = Strongly disagree, 5 = Strongly agree
QA_Testing_Coverage	From 1 to 5 (1 = Strongly disagree, 5 = Strongly agree), does the use of AI in software testing improve test coverage?	1 = Strongly disagree, 5 = Strongly agree
QA_Reporting_quality	From 1 to 5 (1 = Strongly disagree, 5 = Strongly agree) do you agree that AI-generated quality reports are better than manual-generated ones?	1 = Strongly disagree, 5 = Strongly agree
HR_recruiting	From 1 to 5 (1 = Strongly disagree, 5 = Strongly agree), do you agree that AI has supported your organization's recruitment processes (reducing bias, screening cv, etc)?	1 = Strongly disagree, 5 = Strongly agree
HR_onboarding	From 1 to 5 (1 = Strongly disagree, 5 = Strongly agree), do you agree that AI has supported your organization's recruitment processes (reducing bias, screening cv, etc)?	1 = Strongly disagree, 5 = Strongly agree
HR_performance	From 1 to 5 (1 = Strongly disagree, 5 = Strongly agree), do agree that AI contributes to monitoring and improving employee performance metrics?	1 = Strongly disagree, 5 = Strongly agree
PM_Risks	From 1 to 5 (1 = Strongly disagree, 5 = Strongly agree), do you agree that AI has helped identify project risks?	1 = Strongly disagree, 5 = Strongly agree

PM_Schedules	From 1 to 5 (1 = Strongly disagree, 5 = Strongly agree), do you agree that AI facilitates the generation of project timelines and schedules?	1 = Strongly disagree, 5 = Strongly agree
PM_Communication	From 1 to 5 (1 = Strongly disagree, 5 = Strongly agree), do you agree that AI has facilitated communication between project stakeholders?	1 = Strongly disagree, 5 = Strongly agree
AI_Challenges	What are the primary challenges in integrating AI into the software development lifecycle?	
AI_Motivation	What are the main motivations for adopting AI in your organization?	
AI_Adoption	From 1 to 5 (1 = Strongly disagree, 5 = Strongly agree), do you agree that your organization is ready to adopt AI?	1 = Strongly disagree, 5 = Strongly agree
AI_Support	From 1 to 5 (1 = Strongly disagree, 5 = Strongly agree) do you agree that top management's support is important for successful AI adoption?	1 = Strongly disagree, 5 = Strongly agree
AI_investment	From 1 to 5 (1 = Strongly disagree, 5 = Strongly agree) do you agree that your organization will increase its investment in AI in the next two years?	1 = Strongly disagree, 5 = Strongly agree

Table 33: List of Variables

Author's Statement:

I hereby declare that, in accordance with article 8 of Law 1599/1986 and article 2.4.6 par. 3 of Law 1256/1982, this thesis/dissertation is solely a product of personal work and does not infringe any intellectual property rights of third parties and is not the product of a partial or total plagiarism, and the sources used are strictly limited to the bibliographic references.