“Assessing the impact of artificial intelligence on project efficiency enhancement”

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ASSESSING THE IMPACT OF ARTIFICIAL INTELLIGENCE ON PROJECT EFFICIENCY ENHANCEMENT

Abstract

The study explores the impact of artificial intelligence (AI) technologies on project management (PM) across different industries. It aims to assess how AI adoption in PM affects project efficiency. The study surveyed 159 project supervisors and specific project managers implementing projects from 7 industries in the Republic of Kazakhstan: software, green energy, engineering, construction, science, transport, and tourism. The research used variance and linear regression analyses to evaluate the relationship between AI adoption and project efficiency level measured by the Likert scale from 1 to 5 and test the associated hypotheses. The results show that AI adoption varies among industries, with software, construction, and scientific projects being the most active users. The study also found that the use of AI differed across eight project performance domains, with the stakeholder domain using voice technologies and process automation and the uncertainty domain using fewer tools. Projects with higher AI adoption rates showed higher efficiency scores (for example, in Software projects, the AI adoption rate is 3.2; the efficiency rate is 3.3), while those with lower efficiency levels (for example, in the Tourism industry, the AI adoption rate is 1.9; the efficiency rate is 2.2) showed the worst results. Decision-making systems, process automation, and voice technologies are the three most critical AI technologies PM professionals use to improve project efficiency.

Keywords artificial intelligence, project management, PMBOK standard, project performance domains, Kazakhstan

JEL Classification O32, D83, M10

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INTRODUCTION

Project implementation across various industries faces threats and risks due to a rapidly changing business environment (PMI, 2023). Achieving project efficiency becomes challenging due to the difficulties that arise from increasing complexity, communication gaps, and human resource management issues (Turner, 2021; Narbaev, 2022). Modern projects involve multiple interdependent stakeholders, global teams, large datasets, and rapidly changing requirements, which traditional tools cannot manage efficiently (De Marco, 2021; Zhidebekkyzy et al., 2019). This problem underscores the urgent need to adopt new knowledge-based approaches to effectively manage projects (P. Daniel & C. Daniel, 2018).

In this regard, Artificial Intelligence (AI) is one of the enabling technologies successfully implemented at various levels of knowledge-based PM in recent years (Bodea et al., 2020). The integration of AI into the organizational PM framework is a transformative trend that reshapes the way how projects are implemented in various industries (Müller et al., 2024). Project Management Institute (PMI, 2019), one of the leading organizations that advocate the PM profession, emphasizes the role of AI in PM in the successful and timely completion of a project. Therefore, project managers actively apply AI that radically improves project planning and execution processes, optimizes project duration, and reduces project costs (Shang et al., 2023).

Even though the project implementation witnesses increasing automation of project tasks and their management processes (Friedrich, 2021), adopting AI technologies in this field still needs to be well-researched (Bodea et al., 2020). Due to the lack of empirical investigations regarding AI applications in the field, the impact of AI on project success still needs to be examined (Singh & Haju, 2022; Fridgeirsson et al., 2021). Also, the literature lacks studies that evaluate the application of AI methodologies across various management domains of the PM field (Müller et al., 2024). By investigating the impact of AI on project efficiency, researchers and practitioners can identify best practices and standards for integrating AI into PM frameworks like PMBoK methodology (Jariwala, 2024).Therefore, understanding this relationship can provide actionable insights to improve outcomes across industries.

1. LITERATURE REVIEW

The literature review explores the conceptual framework of AI, including its classifications and applications within PM.

The term "artificial intelligence" was first defined in 1956 by American scientist John McCarthy, who stated that AI is a field of computer science concerned with creating systems capable of performing tasks that require human intelligence, such as learning, speech recognition, decision-making, and problem-solving (EB, 2024). The capacity of AI to analyze extensive datasets and deliver predictive insights has significantly transformed decision-making processes in PM (Letkovsky et al., 2023). AI systems leverage historical data and machine learning algorithms to anticipate project risks, develop schedules, and optimize resource allocation (Awad, 2024). By leveraging AI technology, project managers enhance their data analytics capabilities, improve prediction accuracies, and streamline workflows, thereby achieving more effective project delivery and boosting organizational competitiveness (Sahadevan, 2023).

One of the initial studies on AI application in PM stated that AI was a form of cognitive support and proposed that such technologies could augment and expand the functionalities of computer-based PM systems (Levitt & Kuntz, 1987; Cubric, 2020). From the outset, it was evident that AI could be effectively used in PM to examine large datasets and improve the reliability of project cost estimates (Narbaev et al., 2024; Warburton et al., 2023). Earlier studies reported that the promising PM areas where AI can be implemented were project scheduling with limited resources conducted during the project planning phase, as well as time, cost, and risk management. The main benefits of AI applications were improving the hard-skills box of project managers and teams, focusing on improving the computing capabilities of the PM system.

In the recent PM literature, AI refers to the emulation of human cognitive functions by machines, mainly through computer systems (Shoushtari et al., 2024; Tarasenko et al., 2024). AI's primary benefits lie in optimizing repetitive and low-value tasks, therefore enabling project managers to focus on more strategic responsibilities (Gusti et al., 2024). As noted by Mariani and Mancini (2023), AI can enhance productivity by automating mundane tasks, allowing managers to devote more attention to team management and value creation. These efficiencies extend to resource allocation and scheduling, where AI-driven tools can minimize waste and improve project delivery (Savio & Ali, 2023), including various types of projects, such as infrastructure and public-private partnership projects (Samoilov et al., 2024). This allows project managers to improve their soft skills and focus more on behavioral aspects and teamwork in the project environment.

For a comprehensive understanding of AI's role and functions, it is essential to classify them. Table 1 presents some of the widely used classification areas (functionality, learning class, application area, and capability) of AI.

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Table 1. Classification of AI technologies in the literature

Classification by	AI tool	Description	Example
Functionality	Machine learning (ML)	Uses algorithms to learn from and make decisions based on data (Kukshev, 2020)	Decision trees, neural networks, and support vector machines
	Decision-making systems	Simulates human expertise and decision-making, often used in diagnostics and fault detection (Zhao et al., 2020)	MYCIN (medical diagnosis), DENDRAL (chemical analysis), IBM Watson, Protege
	Robotics and automation	Interacts with the physical world, performing tasks autonomously based on AI decision-making capabilities (Veshneva, 2023)	Industrial robots, drones, humanoid robots
	Limited memory	Uses past experiences to make better decisions (Russell & Norvig, 2016)	Self-driving cars, AI-powered navigation systems
	Natural language processing (NLP)	It allows machines to process, understand, and generate natural language text or speech (Jurafsky & Martin, 2021)	Chatbots, Machine Translation (Google Translate), Sentiment Analysis
Learning class	Supervised learning	The model is trained on a labeled dataset where each training example is paired with an output label (Géron, 2019)	Spam detection, SpamSpy, MailCleaner
	Unsupervised learning	Training on data without labeled outputs, focusing on identifying patterns or groupings (Xu & Wunsch, 2010)	Customer clustering, Optimove, Peak.ai
	Semi-supervised learning	Combines a small amount of labeled data with a large amount of unlabeled data during training (Engelen & Hoos, 2019)	Intelligent assistants or autonomous vehicles (Chat GPT)
Application area	Medical AI systems	Used for diagnosis, prognosis, and treatment optimization, often in imaging and personalized medicine (Alam et al., 2019; Topol, 2019)	IBM Watson for oncology
	Education and tutoring systems	used for personalized learning, intelligent tutoring systems, and student performance tracking (Vaerenbergh & P'erez-Suay, 2021)	Talent learning management system (LMS)
Capability	Narrow AI	Designed to perform specific tasks, such as facial recognition, speech recognition, or game-playing (Mitchell, 2019)	Virtual assistants like Siri, Google Assistant, IBM Watson
	General AI	A theoretical concept where machines can perform any intellectual task that a human can (Bostrom, 2014)	These concepts are hypothetical and remain a future goal
	Super AI	Referred to as Artificial Superintelligence (ASI), surpasses human intelligence in all aspects (Bostrom, 2014)	

As shown in Table 1, there are a vast number of AI tools, and specifying which AI technologies are suitable for a particular performance domain of PM is a challenge (Cubric, 2020; Bodea et al., 2020). Table 2 presents the top 10 most used AI tools in PM, as limited to the ten most recent studies in the field. These tools are further examined in this study.

As shown in Table 2, PA emerges as the most frequently used AI tool, identified in five studies. This suggests that it is a significant focus in the litera-

Table 2. Frequently mentioned AI tools in the PM literature

No.	Study	PA	KBS	DMS	VT	VA	IVP	ML	RO	TM	CV
1	Sanchez et al. (2020)	–	+	+	+	–	–	–	–	–	–
2	Zhang (2020)	–	+	–	–	–	–	–	+	–	–
3	Fridgeirsson et al. (2021)	+	–	–	–	+	–	+	–	+	–
4	Lokhande (2022)	–	+	–	+	–	+	–	–	–	–
5	Sahadevan (2023)	–	–	+	–	+	+	–	+	+	+
6	Wang (2023)	+	+	+	+	+	+	–	–	–	–
7	Oliveira et al. (2023)	+	+	+	–	+	–	–	–	–	–
8	Mariani and Mancini (2023)	+	–	–	+	+	–	+	–	–	–
9	Shoushtari et al. (2024)	+	+	–	–	–	+	–	–	–	–
10	Rafee et al. (2024)	+	–	+	+	–	+	+	+	–	–
	Total	6	6	5	5	5	5	3	3	2	1

Note: PA – process automation, KBS – knowledge-based systems, DMS – decision-making systems, VT – voice technologies, VA – virtual agents, IVP – image and video processing, ML – machine learning, RO – robotics, TM – theory of mind, CV – computer vision.

ture, reflecting its widespread applicability and importance in streamlining PM processes by reducing manual effort and enhancing efficiency. KBS and DMS are investigated in four studies. They are used to improve PM outcomes by providing data-driven insights and aiding in more informed decision-making. VT, VA, and IVP also show promise, while specialized areas like TM, RO, and CV appear to be more niche. This distribution highlights the diverse applications and evolving focus areas of AI in PM. Next, the AI tools mentioned in at least 5 studies are selected as a variable for the analysis. Because the AI with multiple citations is likely associated with significant results, making them relevant to the study.

In response to the emergence of new agile methodologies and the necessity for projects to adapt to dynamic changes, PMI released the seventh edition of the PMBoK Guide. This updated edition shifts the focus from processes and deliverables, as emphasized in previous versions, to a value delivery approach. It focuses on achieving unique goals, considering the complexity of the environment and stakeholder interests that combine to ensure project success (Mosalaesi & Laryea, 2024). This professional guide introduces a revised project performance system that delineates eight PPDs, reflecting the new emphasis. PPDs are interrelated activities that are vital in successfully implementing project objectives. They cover stakeholder engagement, team management, choosing a development and project life cycle approach, planning and executing tasks, ensuring the delivery of results, evaluating performance, and managing risks (PMBoK, 2021). The independent and interactive domains work together to achieve the project's intended objectives (Amaro & Domingues, 2023). Table 3 provides a brief description of these domains.

A literature review found that the 7th edition of the PMBoK manual replaced the ten knowledge areas presented in the 6th edition with eight performance domains. Therefore, the level of adoption of these eight domains shows the current trends in the PM profession and project environment. The 8 PPDs are selected as independent variables in this study.

Further literature analysis focuses on AI's impact across 8 domains among different industries. For instance, Pospieszny et al. (2018) stated that AI techniques accurately estimate the effort required in software projects. Automation through AI allows software project managers to enhance overall productivity because AI is supported by software (Friedrich, 2021). Moreover, AI tools are often the results of software projects, so their active use during the implementation of such projects is obvious (Inan et al., 2022).

Further, the literature analysis shows specific AI tools for each PM performance domain depending on the purpose of AI. For example, a crucial task of a project manager is project plan-

Table 3. PPDs, as per the PMBoK guide

Source: PMI (2021).

No.	Project performance domains	Description
1	Stakeholder	Represents a core aspect of effective PM, emphasizing the strategic engagement of stakeholders and the optimization of outcomes through comprehensive analysis
2	Team	Essential in PM, concentrating on team dynamics, leadership effectiveness, and the development of a productive team culture.
3	Life cycle	Emphasizes the selection and implementation of the most appropriate methodologies for project execution and oversight
4	Planning	Crucial for establishing the groundwork for a project's success, concentrating on the strategic alignment of resources, timelines, and team dynamics with project objectives
5	Project work	It centers on the execution phase of project management, during which planning activities are implemented, and project deliverables start to materialize
6	Delivery	It focuses on the culmination of project efforts, with an emphasis on delivering value to stakeholders, managing deliverables, and ensuring the quality of the final outcomes
7	Measurement	Crucial in PM, concentrating on the systematic tracking and analysis of project progress in relation to its established objectives
8	Uncertainty	Addresses the intrinsic unpredictability and complexity involved in managing projects

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ning (planning PPD), which emphasizes activity scheduling and time management (De Marco et al., 2016; Ottaviani et al., 2024). AI assists project teams in optimizing project schedules, monitoring work implementation, and forecasting project duration (Somasundaram, 2020; Chou et al., 2010). AI-powered solutions like chatbots and virtual assistants enhance team member engagement and communication, leading to a smoother and more effective project execution, which improves the PM delivery performance domain (Sahadevan, 2023). Also, the PA's ability to process and analyze large volumes of data sufficiently improves decision-making processes and is used in project monitoring and control (De Marco et al., 2024), facilitating the PM measurement performance domain (Jariwala, 2024).

AI is often used by project managers for uncertainty analysis and risk management tasks (Martínez & Fernández-Rodríguez, 2015; Afzal et al., 2021; De Marco et al., 2016) and they are part of the PM uncertainty performance domain. Fridgeirsson et al. (2021), who worked on identifying AI's potential areas of tremendous success, stated that project managers sometimes ignore the possible contribution of AI to the PM measurement performance domain despite its potential opportunities, and AI is not taken seriously in other areas of PM. These findings also show inconsistencies in AI adoption in eight PM performance domains.

Chou et al. (2010) found that AI adoption in PM sufficiently increases the productivity of a project team. Furthermore, AI algorithms can improve project task planning, resource allocation, quality management, and progress tracking, increasing project efficiency (Sabden et al., 2020). However, Somasundaram (2020) noted that projects with low levels of AI adoption often faced costs and schedule delays and reduced project efficiency.

The study identified PA as a critical AI tool because the automation of various project manager functions (e.g., task scheduling, risk analytics, cost forecasting) allows them to enhance project efficiency (Auth et al., 2019; Dam et al., 2018). Also, DMS is the predominant and critical technology regarding project efficiency due to its ability to improve the accuracy of project planning and control (Levitt & Kunz, 1987; Sahadevan, 2023).

Overall, the literature review demonstrates that AI integration into project management enhances productivity, improves forecasting accuracy, and aligns with the "8 domains methodology," establishing AI as a critical resource for driving project efficiency.

Building on these findings, the study aims to evaluate the potential of AI adoption within PM performance domains to enhance overall project efficiency.

Accordingly, the following hypotheses were built:

H1: *The adoption of AI is higher in software projects than in other project types.*

H2: *The adoption of AI varies across the eight PDDs.*

H3: *Projects with a higher AI adoption level have a higher project efficiency level.*

H4: *PA and DMS are critical AI tools to improve project efficiency.*

2. METHODOLOGY

2.1. Survey design and responses collection

The survey is designed to gather quantitative data on how project managers integrate AI into their workflows, enabling a better understanding of current practices and obstacles faced. It is structured into two main sections: general questions, which include questions about the respondents' profiles, and the main section, containing questions about the research problem. The main section consists of 16 questions to assess AI's adoption and impact on PM. The survey contained a mix of question types like multiple-choice questions, rating scale questions, and open-ended questions. Using a five-point Likert scale, the respondents were asked about adopting AI tools in PM performance domains and their impact on project efficiency (see Appendix A).

The data were collected via Google Forms from 159 project managers in Kazakhstan's software, green energy, engineering, construction, science, transport, and tourism industries during three months from February to April 2024.

The survey results were sorted for the datasheet, and questionnaires with incomplete answers were removed. Finally, 159 out of 165 questionnaires were selected for further analysis.

2.2. Respondents profile and reliability test

The pool of respondents was selected from the database of acting project managers of the Union of Project Managers of the Republic of Kazakhstan and the Kazakh Project Management Association. 63 percent of them are project managers and the rest are project supervisors. The survey collected data on the experience levels of participants, revealing a notable concentration of respondents with less than 11 years of experience. A breakdown of the findings is in Table 4.

Table 4. Experience of the respondents

No.	Experience	Number	Percentage
1	Less than 11	138	87
2	11-15	14	9
3	16-20	5	3
4	Higher than 20	2	1
	Total	159	100

The results indicate that a significant majority (over 86%) of respondents are relatively early in their project management careers, with less than 11 years of experience. This suggests that the survey captures perspectives predominantly from newer professionals in the field. On the other hand, it shows the lack of experienced PM managers and the low maturity level of PM in the Republic of Kazakhstan. In contrast, only a tiny fraction of participants (about 13.1%) have over 11 years of experience, highlighting a potential gap in insights from more seasoned project managers. Most of them have PM certificates (35%), master's degrees in PM (34%), and practical experience in running projects (38%).

As shown in Table 5, the research sample covers 7 types of projects. The ratio of projects varies from 11 to 19 percent, which allows the sample size to be considered acceptable for further calculations.

Table 5 shows the varying levels of experience across different project types, with software and green industries being dominated by respondents with less than 11 years of experience, while other industries like construction and science have a more diverse range of experience levels.

Table 6 summarizes the results of the reliability analysis conducted using Cronbach's Alpha for key variables related to AI adoption in PM.

Table 6. Reliability test results

Variables	Cronbach's Alpha score	N	Interpretation
AI adoption	0.9	6	Excellent reliability
Project efficiency	0.81	8	Excellent reliability

The variable measuring AI adoption yielded a Cronbach's Alpha score of 0.9, indicating excellent reliability. This suggests that the items used to assess AI adoption are highly consistent, providing confidence that they effectively capture the construct of interest, whether defined by level, rate, or general adoption.

Table 5. Distribution of respondents by project type and experience level

No.	Project type	Number of responses	Percent of total	Respondents with less than 11 years' experience (%)	Respondents with 11-15 years' experience (%)	Respondents with 16-20 years' experience (%)	Respondents with higher than 20 years' experience (%)
1	Software	21	13	92	8	1	0
2	Green	19	12	93	7	0	0
3	Engineering	31	19	92	4	2	2
4	Construction	19	12	47	30	18	5
5	Science	29	18	53	31	14	2
6	Transport	24	15	80	11	6	3
7	Tourism	16	11	91	9	0	0
	Total	159	100	–	–	–	–

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The variable associated with PM efficiency produced a Cronbach's Alpha score of 0.81, also indicating excellent reliability. This consistent score confirms that the items measuring project management efficiency are reliable and can be used interchangeably in analyses without concern for internal inconsistencies.

The data distribution is assumed to be normal, which is important for the validity of subsequent statistical analyses. This suggests that the items effectively measure the same underlying construct related to the adoption and impact of AI in PM. This shows the study results have a significant level of reliability and validity.

2.3. Research model

The collected data were processed using linear regression among chosen variables.

As shown in Figure 1, the study evaluates the relationship between chosen variables. The independent variables are eight PM performance domains (X1-X10), while the project efficiency level is identified as the dependent variable (Y). The 7 project types act as moderating variables. Finally, the AI tools selected from the literature review (Table 2) serve as mediator variables (A1-A6).

2.4. Results and discussion

Table 7 provides an analysis of the average use intensity of AI in PM domains, project efficiency scores, and their statistical relationships across various industries. The regression analysis was used to quantify the strength and significance of the relationship. It helped to understand how closely the two variables are related and whether this relationship is statistically significant.

Table 7 shows a relatively strong positive linear relationship between the adoption of AI across the PM performance domains and project efficiency level. The regression model is statistically significant (acceptable p-value in 4 industries out of 7), which confirms that the use of AI in PM domains may increase project efficiency.

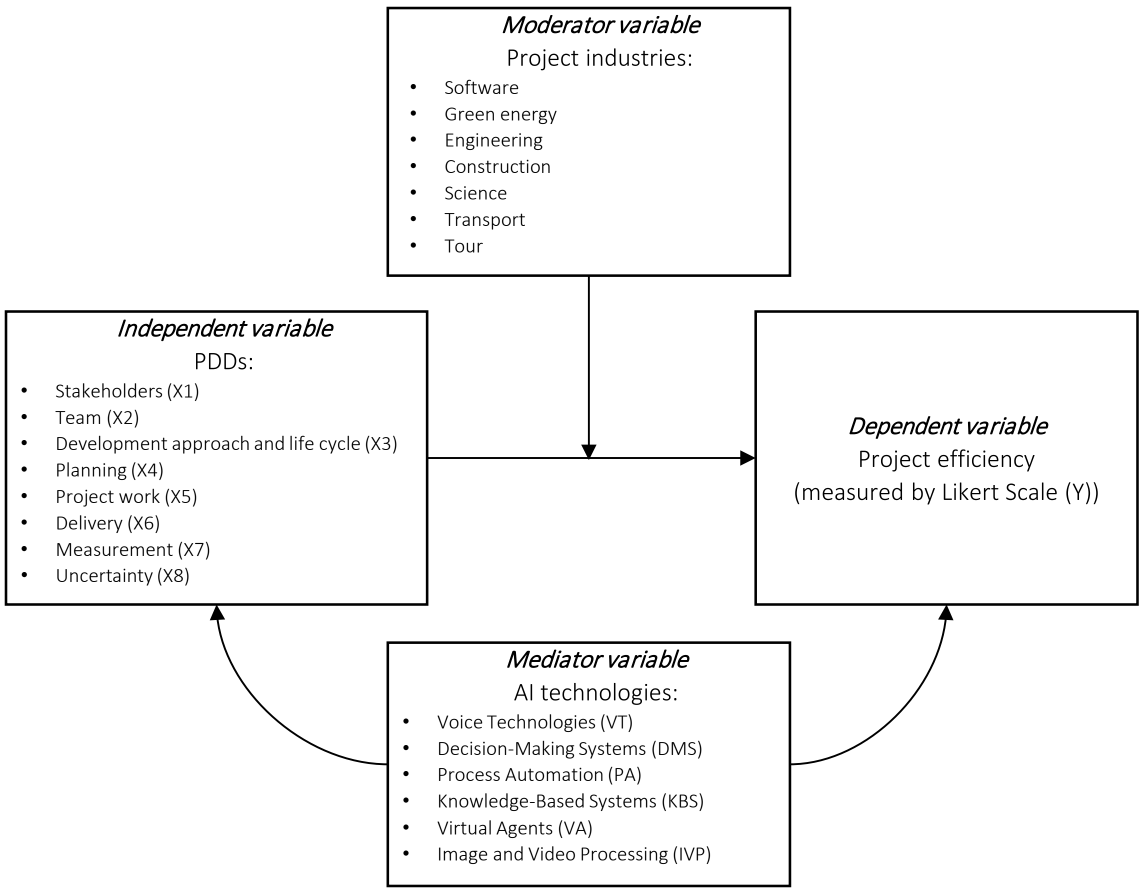

Figure 1. Research model

Table 7. AI adoption and project efficiency by project industries

Industry	AI adoption	Project efficiency, average score	Number	Multiple R	R-square	P-value
Software	3.2	3.3	21	0.4	0.6	0.42
Green	2.7	2.8	19	0.7	0.8	0.02**
Engineering	1.3	2.5	31	0.2	0.5	0.008
Construction	2.7	3.0	19	0.7	0.8	0.001*
Science	2.8	2.9	29	0.9	0.8	0.001*
Transport	2.3	2.7	24	0.7	0.9	0.05**
Tourism	1.9	2.2	16	0.8	0.9	0.94

Note: * $p \le 0.001$, ** $p \le 0.05$ acceptable significance level.

As shown in Table 7, the projects with a high rate of AI adoption, for example, software industry (3.2; 3.3), science (2.8; 2.9), and construction (2.7; 3.0) fields have the highest rate of project efficiency, while the projects with the lowest score of AI implementation in PM like engineering (1.3; 2.5) and tourism industries (1.9; 2.2) have low project efficiency levels. These results may vary among discussed industries due to the specific demands and characteristics of these fields.

Overall, AI's integration into software and scientific projects tends to be more profound and transformative due to the nature of the tasks. Because both industries may be considered producers of AI technologies, in contrast, the specifics of the tourism industry may not require the industry's rapid transformation towards AI technologies. As for engineering projects, perhaps the domestic industry is at the initial stage of transformation towards the use of advanced technologies. AI has not yet had enough time to establish itself there due to the lack of experience of local project managers. These findings support the first hypothesis, H_1: The adoption of AI is higher in software projects than in others.

Figure 2 shows the most used AI technologies by surveyed project managers during the project execution period. PA, DMS, VT, and VA are identified as the most prevalent AI tools utilized in PM. This prominence can be attributed to their extensive range of functionalities and benefits. For example, PA significantly enhances operational efficiency by reducing human error and ensuring consistency in task execution. DMSs support strategic decision-making by providing data-driven insights.

VT contributes to project management through features such as voice-activated project updates, reminders, and hands-free control of project management software, while VAs offer continuous support by automating routine queries and tasks, thereby improving responsiveness and user experience. The widespread adoption of these AI tools underscores their critical role in enhancing various aspects of project management, from task execution and decision-making to communication and support.

Further, Table 8 represents rankings indicating how each AI technology performs in each domain. The adoption of predefined AI technologies was ranked among PM performance domains. Technologies like PA and KBS are highly valued in domains like development, project work, and delivery. At the same time, VT and Image/Video Processing are preferred in stakeholder management and delivery domains. Decision-making sys-

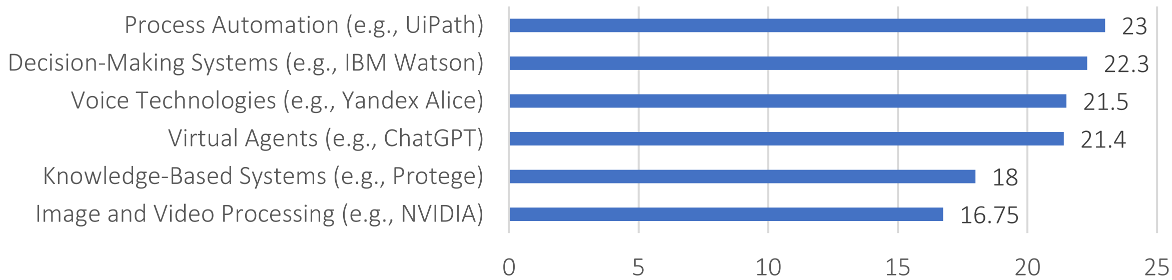

Figure 2. Frequency of using AI tools

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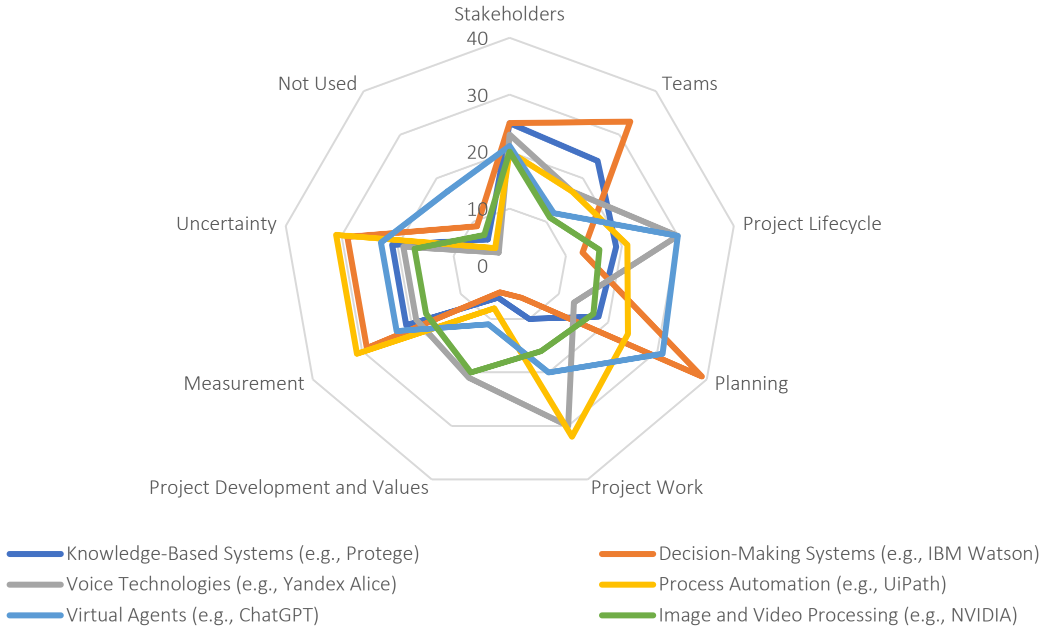

Figure 3. AI adoption score across domains

Table 8. AI technologies adoption ranks among PM performance domains

No.	PM performance domains	VT	DMS	PA	KBS	VA	IVP
1	Stakeholders	1	4	2	6	4	1
2	Team	2	2	6	7	7	5
3	Development, Approach, and Life Cycle	4	6	1	5	2	3
4	Planning	5	1	7	3	1	2
5	Project Work	6	7	1	1	5	4
6	Delivery	7	5	3	8	8	1
7	Measurement	3	3	4	2	3	5
8	Uncertainty	3	5	5	4	6	4

tems and VA also play important roles but vary in effectiveness depending on the domain.

Figure 3 provides a matrix that estimates the AI adoption in various project domains in percentage terms.

As Figure 3 shows, in the team domain, decision-making systems have the highest score (33%), indicating that these systems play a key role in working with teams. They are followed by KBS (24%). In the project life cycle domain, VT (30%) and VA (e.g., ChatGPT) (30%) have the highest scores. It shows their importance in various stages of the project life cycle. The project Work domain is supported by high PA (32%) adoption, while in the project delivery and values domain, VT (21%) is the driving AI tool. These findings support the second hypothesis, H_2: The adoption of AI varies among eight PDDs.

Table 9 summarizes the adoption scores, efficiency scores, and statistical significance (p-values) for AI tools across various domains using linear regression analysis. The P-value assesses whether the relationship between variables is statistically significant.

As Table 9 shows, the domains "Stakeholders," "Measurement," and "Uncertainty" have lower efficiency scores, ranging from 2.7 to 2.9. This may indicate potential problems or weaknesses that require additional attention and improvement, or it may result from a low AI adoption score. Also, the study should consider that the PM field is still in the early stages of AI integration (Mariani & Mancini, 2023), so the AI adoption rate in many domains may still be low.

The domains "Development, Approach and Life Cycle," "Project Work," and "Delivery" have high

Table 9. AI adoption and project efficiency by the PM performance domains

No.	Domains	AI adoption score	Efficiency score	P-value
1	Stakeholders	2.2	2.7	0.28
2	Team	2.4	3.1	0.05*
3	Development, Approach, and Life Cycle	2.5	3.1	0.001*
4	Planning	2.6	3.2	0.78
5	Project Work	2.5	3.1	0.05**
6	Delivery	2.1	2.8	0.001**
7	Measurement	2.2	2.9	0.05**
8	Uncertainty	2.3	2.9	0.92

Note: * $p \leq 0.05$; ** $p \leq 0.001$.

statistical significance ($p \leq 0.001$), which emphasizes their importance and the significant relationship with the efficiency rate. Moreover, these domains are distinguished by a high level of AI implementation. In turn, these findings show that AI adoption rates vary among domains, and projects with high AI adoption rates achieve higher efficiency. This statement endorses the third hypothesis, *H3:* Projects with higher AI adoption have a higher efficiency level.

Table 10 presents the critical AI technologies for performance domains that enhance the efficiency of projects.

As Table 10 shows, the relevant/critical AI tools with high p-values for each PM domain were identified. As shown, the decision-making systems play a critical role in enhancing project efficiency. This AI tool is essential within the stakeholder, team, planning, measurement, and uncertainty domains. These systems provide actionable insights and support more informed evaluations and assessments.

Process automation is essential for planning, project work, measurement, and uncertainty domains. It may be due to its ability to automate the collection and processing of data, reduce human error, and contribute to more accurate and timely evaluations. Moreover, automating routine processes helps reduce the time needed to complete repetitive tasks in PM. These results support the fourth hypothesis, stating that *H4:* PA and DMS are critical AI tools to improve project efficiency.

An interesting finding is that voice technologies show high significance in four domains, indicating their versatile use in PM. It may be due to their ability to facilitate communication and interaction within teams, support various stages of development, and contribute to project work by enabling voice-activated updates and reminders.

Data analysis revealed a strong correlation between AI utilization and improved performance in development, project life cycle, task execution, and delivery. These findings, which are in line with previous studies such as Mariani and Mancini (2023), highlight the transformative potential of AI in PM, even in its early stages of integration. Moreover, the study confirmed that projects with high AI implementation, such as software and scientific research, have higher success rates. It may be because the combination of task complexity, familiarity with AI, and access to resources enables software and scientific research projects to leverage AI effectively. Because both industries may be considered producers of AI

Table 10. Rank of critical AI tools for enhancing project efficiency

No.	AI tools	Stakeholder	Team	Life Cycle	Planning	Project Work	Delivery	Measurement	Uncertainty	Sum
1	Decision-Making Systems	+	+		+			+	+	5
2	Process Automation				+	+		+	+	4
3	Voice technologies	+		+		+	+			4
4	Knowledge-Based Systems		+					+	+	3
5	Virtual Agents			+	+					2
6	Image and Video Processing	+					+			2

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technologies, in contrast, the specifics of the tourism industry may not require the industry's rapid transformation towards AI technologies. As for engineering projects, perhaps the domestic industry is at the initial stage of transformation towards using advanced technologies (Akhmedov et al., 2022). AI has not yet had enough time to establish itself there due to the lack of experience of local project managers. Moreover, these industries often contribute directly to AI innovation, allowing them to integrate cutting-edge AI technologies seamlessly into their workflows.

Besides, despite the benefits, the AI adoption rate in the tourism industry may be slower in smaller enterprises due to cost constraints and a lack of technical expertise. At the same time, challenges such as high implementation costs and a shortage of skilled personnel can impede widespread AI integration in the construction industry. The low adoption rate in areas such as tourism and engineering may be due to the lack of experience of project managers, highlighting the need for additional educational initiatives.

Current results indicate that AI adoption varies across industries. For example, the low adoption rate in tourism (1.9; 2.2) is explained by the less critical need for AI technologies in this industry. This highlights the importance of understanding and addressing industry-specific needs when it comes to AI adoption.

The importance of voice technologies in four project management areas, including stakeholder management, project life cycle, task execution, and delivery, is consistent with the findings of Jariwala (2024), who highlight the positive relationship of mentioned technologies with PM domains. In addition, voice technologies facilitate seamless communication among stakeholders, regardless of location, by enabling voice calls, virtual assistants, or AI-driven voice bots.

Process automation and decision support systems were found to be critical tools for improving efficiency. Jariwala (2024) presents similar results, noting that PA is a key tool for reducing routine operations and improving data accuracy, and DMS is a key technology for increasing efficiency. However, some critiques highlight potential drawbacks. A study analyzing automated decision support systems identified issues such as the lack of standardized algorithms, which can hinder their effective implementation and slow down their adoption in management practices (Tikhanychev, 2022). Additionally, over-reliance on automation may lead to reduced human oversight, potentially resulting in unforeseen errors or ethical concerns.

The findings confirm that integrating AI into project management improves key performance indicators. This highlights the need for further research and advancement of AI technologies across industries, especially those where adoption remains low. Such research provides a foundation for developing more effective strategies for implementing AI into project management.

CONCLUSION

The study aimed to examine AI adoption in PM by assessing its use across 8 PPDs and its impact on project efficiency. The results show that AI enhances project efficiency, with its impact varying across different industries and project types. Projects with mature AI adoption demonstrate a high level of efficiency. Moreover, the level and maturity of AI adoption differ among the eight PPDs.

Therefore, the study concludes that to achieve high efficiency during project implementation, project supervisors need to actively use critical AI tools identified during this study. The comprehensive use of appropriate AI tools in each PM domain sufficiently increases project efficiency.

AUTHOR CONTRIBUTIONS

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APPENDIX A

Dear participants,

The purpose of this survey is to assess the level of adoption and impact of artificial intelligence in projects in Kazakhstan. The questions are based on the 8 PMBOK Performance Domains. The survey is part of a research project supported by the Kazakh-British Technical University and funded by the Ministry of Science and Higher Education of Kazakhstan.

The survey will take approximately 10-12 minutes. Required fields are marked with an asterisk (*).

Privacy and Data Use:
We respect your privacy. All data provided will be analyzed in aggregate form and used solely for research purposes.

Thank you for participating in our survey.

SECTION 1. General questions

Which of the following options best describes your level of skill in project management?

- ☐ Master in Project Management
- ☐ PM Certifications (PMP, PRINCE2 and etc.)
- ☐ Project Manager experience

Highlight your position in project:

- ☐ Project supervisor
- ☐ Project manager
- ☐ Other (**Note: If you do not hold one of the above positions, please skip the questionnaire*)

Scientific and/or industrial experience in the field of PM:

- ☐ Less than 11 years
- ☐ 11-15 years
- ☐ 16-20 years
- ☐ More than 20 years

What area of activity does your project belong to?

- ☐ Education and Science
- ☐ Engineering
- ☐ IT & Software
- ☐ Communications
- ☐ Service
- ☐ Industry
- ☐ Transport
- ☐ Tourism
- ☐ Construction
- ☐ Green Energy
- ☐ Other (write your answer)

Please indicate the frequency of use of each type of artificial intelligence from 0 to 5, where:
0 – Never, 1 – Very rarely, 2 – Rarely, 3 – Often, 4 – Quite often, 5 – Always

- ☐ Knowledge-based systems
- ☐ Decision Management
- ☐ Voice assistant
- ☐ Speech recognition
- ☐ Robotic Process Automation
- ☐ Expert systems
- ☐ Virtual agents
- ☐ GPUs
- ☐ Face recognition
- ☐ Conversational Computing
- ☐ Deep learning
- ☐ Natural Language Generation
- ☐ Your option

Please indicate in which of the UP Execution Domains (8 Execution Domains according to PMBOK) you use a specific type of artificial intelligence*

AI tool	Not using	Stakeholders	Teams	Lifecycle	Planning	Project Management	Transmission	Uncertainty
Knowledge-based systems (approx. Protege)								
Decision making (approx. IBM Watson)								
Voice technologies (approx. Yandex Alice)								
Process automation (approx. UIPath)								
Virtual agents (approx. ChatGPT)								
Image and video processing (approx. NVIDIA)								

SECTION 2. PMBOK 8 domains

Welcome to the survey section assessing the adoption and impact of artificial intelligence in projects according to the 8 Execution Domains of the Project Management Body of Knowledge (PMBOK). This section presents 16 questions, 8 of which are aimed at measuring the level of influence of artificial intelligence tools on project management through the effectiveness of use, and the remaining 8 questions assess the level of implementation of artificial intelligence in project management (PM), taking into account the frequency of their use.

1. Stakeholders (adoption)

Assess how often you use artificial intelligence tools to analyze and manage stakeholder expectations in your projects.
Rate from 0 to 5, where:
0 – Never, 1 – Very rarely, 2 – Rarely, 3 – Moderately, 4 – Often, 5 – Very often.

1.1. Stakeholders (impact)

Evaluate the effectiveness of applying artificial intelligence to interact with stakeholders in the field of project management.

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Rate from 0 to 5, where:
0 – Not used, 1 – Very low, 2 – Low, 3 – Moderate, 4 – High, 5 – Very high.

2. Team (adoption)

Assess the frequency of artificial intelligence use on team dynamics and collaboration in project teams.
Rate from 0 to 5, where:
0 - Never, 1 - Very rarely, 2 - Rarely, 3 - Moderately, 4 - Often, 5 - Very often.

2.1. Team (impact)

Evaluate the effectiveness of using artificial intelligence tools to manage tasks and distribute workload in these teams.
Rate from 0 to 5, where:
0 – Not used, 1 – Very low, 2 – Low, 3 – Moderate, 4 – High, 5 – Very high.

3. Project life cycle (adoption)

Assess the frequency of application of artificial intelligence to project development methodologies, life cycle approaches, and project management process management.
Rate from 0 to 5, where:
0 – Never, 1 – Very rarely, 2 – Rarely, 3 – Moderately, 4 – Often, 5 – Very often.

3.1. Project life cycle (impact)

Evaluate the effectiveness of artificial intelligence in project development methodologies, life cycle approaches, and project management processes management.
Rate from 0 to 5, where:
0 – Not used, 1 – Very low, 2 – Low, 3 – Moderate, 4 – High, 5 – Very high.

4. Planning (adoption)

Assess the frequency of application of artificial intelligence in the planning and scheduling of project activities.
Rate from 0 to 5, where:
0 - Never, 1 - Very rarely, 2 - Rarely, 3 - Moderately, 4 - Often, 5 - Very often.

4.1. Planning (impact)

Evaluate the effectiveness of artificial intelligence in project planning processes
Rate from 0 to 5, where:
0 – Not used, 1 – Very low, 2 – Low, 3 – Moderate, 4 – High, 5 – Very high.

5. Design work (adoption)

Evaluate how often AI is used to automate repetitive tasks and workflows in your projects.
Rate from 0 to 5, where:
0 – Never, 1 – Very rarely, 2 – Rarely, 3 – Moderately, 4 – Often, 5 – Very often.
5.1. Project work (impact)

Evaluate the effectiveness of using artificial intelligence to automate repetitive tasks and workflows in your projects.

Rate from 0 to 5, where:
0 – Not used, 1 – Very low, 2 – Low, 3 – Moderate, 4 – High, 5 – Very high.

6. Performance assessment (adoption)

See how often you use AI to optimize resource provisioning and meet delivery deadlines
Rate from 0 to 5, where:
0 – Never, 1 – Very rarely, 2 – Rarely, 3 – Moderately, 4 – Often, 5 – Very often.

6.1. Performance assessment (impact)

Evaluate the effectiveness of artificial intelligence on the timely and successful delivery of project results.
Rate from 0 to 5, where:
0 – Not used, 1 – Very low, 2 – Low, 3 – Moderate, 4 – High, 5 – Very high.

7. Transmission (adoption)

Assess the frequency of use of artificial intelligence in assessing the performance of teams and individual project participants
Rate from 0 to 5, where:
0 – Never, 1 – Very rarely, 2 – Rarely, 3 – Moderately, 4 – Often, 5 – Very often.

7.1. Transmission (impact)

Evaluate the effectiveness of artificial intelligence in assessing the performance of the team and individual project participants
Rate from 0 to 5, where:
0 – Not used, 1 – Very low, 2 – Low, 3 – Moderate, 4 – High, 5 – Very high.

8. Uncertainty (adoption)

Assess the frequency with which artificial intelligence is used for scenario planning and risk analysis in uncertain project scenarios.
Rate from 0 to 5, where:
0 – Never, 1 – Very rarely, 2 – Rarely, 3 – Moderately, 4 – Often, 5 – Very often.

8.1. Uncertainty (impact)

Evaluate the effectiveness of using artificial intelligence to manage uncertainty in projects
Rate from 0 to 5, where:
0 – Not used, 1 – Very low, 2 – Low, 3 – Moderate, 4 – High, 5 – Very high.

Please describe the main problems and barriers to implementing artificial intelligence in your activities:

- ☐ Lack of experience and qualifications
- ☐ Lack of access to data
- ☐ Financial aspects
- ☐ Technological unreadiness
- ☐ Your option (please provide)

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