Review

Challenges of Integrating Artificial Intelligence in Software Project Planning: A Systematic Literature Review

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Abstract: Artificial intelligence (AI) has helped enhance the management of software development projects through automation, improving efficiency and enabling project professionals to focus on strategic aspects. Despite its advantages, applying AI in software development project management still faces several challenges. Thus, this study investigates key obstacles to applying artificial intelligence in project management, specifically in the project planning phase. This research systematically reviews the existing literature. The review comprises scientific articles published from 2019 to 2024 and, from the inspected records, 17 papers were analyzed in full-text form. In this review, 10 key barriers were reported and categorized based on the Technology–Organization–Environment (TOE) framework. This review showed that eleven articles reported technological challenges, twelve articles identified organizational challenges, and six articles reported environmental challenges. In addition, this review found that there was relatively little interest in the literature on environmental challenges, compared to organizational and technological barriers.

Keywords: project management; project planning; artificial intelligence; machine learning; TOE framework; software development projects; information technology

1. Introduction

The history of project management is extensive and diverse, spanning many fields. It has played a crucial role in achieving significant milestones, from constructing famous landmarks to breakthroughs in technology and space exploration. According to [1] project management involves the utilization of knowledge, capabilities, tools, and methods to meet specific requirements. This comprehensive approach includes identifying needs, engaging stakeholders, and managing resources while navigating the scope, schedule, cost, quality, and risk constraints [1].

The adoption of artificial intelligence (AI) has significantly transformed project management, particularly owing to the digital transformations necessitated by the global pandemic in 2020 [2]. In addition, AI has helped enhance project management through automation, improving efficiency and enabling project professionals to focus on strategic aspects, particularly in IT and software development projects. This transformation includes the application of AI to resource allocation, risk management, and enhancing communication within teams. Furthermore, it reveals the need for project managers to develop new skills and adapt to an AI-driven environment, emphasizing the importance of training and incorporating AI technologies effectively into organizational cultures [2].

Artificial intelligence (AI) can be broadly defined as machine simulation of human intelligence, aiming to mimic human cognitive processes and behaviours [3]. It includes the ability to learn, solve problems, and make decisions. According to ref. [3,4], AI encompasses both the creation of intelligent machines that can perform tasks requiring human intelligence and the development of systems that can think and act, whether by emulating human behaviour or through unique, non-biological processes. This field spans from narrow AI, designed for specific tasks, to general AI, capable of handling any cognitive task like a human [4].

2. Previous Work

Integrating artificial intelligence into project management has directly affected the phases of project management. Project planning is an important phase in this regard. Project planning is a crucial stage in managing a project. It aims to define the project's goals and outline the steps to achieve them [1]. This phase involves creating a detailed plan that includes:

- Scope management plan: How the project's scope is defined, tracked, and confirmed.
- Requirements management plan: The approach for analyzing, documenting, and managing project requirements.
- Schedule management plan: Guidelines for developing and overseeing the project timeline.
- Cost management plan: Strategies for planning and managing project costs.
- Quality management plan: Processes for ensuring project quality meets the objectives.
- Resource management plan: Planning for estimating and managing project resources.
- Risk management plan: Procedures for identifying and addressing project risks.
- Stakeholder engagement plan: Approaches for involving stakeholders and managing their expectations.
- Communications management plan: Plans for sharing information with stakeholders.
- Procurement management plan: Methods for handling procurement from planning to contract completion.

Each component is essential for guiding the project team towards successful project completion. With the advent of the agile framework in project management, planning has become an iterative process emphasizing adaptability to change and stakeholder feedback throughout a project's lifecycle [1]. Agile planning breaks the project into manageable segments or sprints, enabling flexibility and continuous adjustment based on ongoing feedback and project evolution [1]. The essential elements of agile planning include agile release planning, iteration planning, frequent quality and review steps, and active stakeholder engagement. This approach facilitates a dynamic, value-focused, and collaborative planning environment, ensuring that projects can swiftly adapt to changes and deliver incremental value [1].

The launch of PMI Infinity by the Project Management Institute (PMI) on 19 January 2024 marked a significant advancement in integrating artificial intelligence into project management. This AI-powered knowledge base uses OpenAI's advanced GPT architecture to provide reliable solutions and suggestions for addressing project management challenges. It features a conversational interface that draws from PMI's extensive content library. This development highlights the growing role of AI in project management, prompting the need for research into the challenges of AI in planning software and information technology (IT) projects.

Two literature reviews have attempted to address the challenges of applying AI in project management. Ref. [5] explored the challenges of AI implementation in project management. This review identified several challenges of integrating AI in project management, including the scarcity of data, the high costs associated with AI implementation, the risk of job displacement, and the need for highly skilled technical personnel. In addition, this review showed that system integration and interoperability are significant hurdles. However, the study covered generally all project process groups and paid less attention to the planning phase, which is the most important phase in the project management process.

Another literature review conducted by [3] highlighted the challenges of integrating AI in project management, such as creating comprehensive frameworks that include various project domains, sustainability, and security. They highlighted the lack of research on successfully adopting AI in these crucial areas. In addition, the need for project managers with skills that complement AI's capabilities is emphasized, suggesting that human skills in team and stakeholder management remain vital and are less likely to be replaced by AI. However, it provides a broader overview of AI's applicability and benefits across various project management domains and industries, demonstrating an expansive and multidisciplinary interest in the topic [3].

As a result, this review is essential for offering a cutting-edge review of all the challenges associated with integrating AI into software development projects during the project planning phase. By examining these obstacles, this paper makes a distinctive and timely addition to the body of knowledge on project management. In addition, this review focuses mainly on the planning phase of the project management process, which has different activities that can be integrated with AI. Other papers such as [3] have focused generally on different phases with less attention to planning. Additionally, the present review will assist scholars, decision-makers, and managers who are eager to learn more about this exciting technology in evaluating AI's feasibility for the project management field. Furthermore, this review categorized the issues that were found into technological, organizational, and environmental contexts using the Technology–Organization–Environment (TOE) framework [6]. The TOE is an analytical model that helps understand how organizations adopt technological innovations [6]. It examines technological factors which are the internal and external technologies affecting operations. The organizational factors which represent the characteristics and resources of the organization. In addition, the environmental factors describe the broader context in which the organization operates, including regulatory policies and market trends [6]. This framework is valuable for analyzing the adoption of new technologies, considering the interplay between technology capabilities, organizational readiness, and external pressures [6]. This is how the rest of the paper is organized: The methodology for searching and filtering articles is defined in Section 3. Section 4 concentrates on analyzing and presenting the findings obtained from the selected articles. The results are followed by the discussion in Section 5. Finally, Section 6 discusses the study's restrictions and challenges, as well as future research.

3. Materials and Methods

This study set out to answer the following research question: 'What are the challenges of artificial intelligence in planning IT/software projects?' This research question guided the entire review process, including determining its content and structure, designing strategies for locating and selecting relevant studies, critically evaluating these studies, and analyzing their results. The methodological approach was carefully crafted to ensure a comprehensive understanding and assessment of the challenges posed by AI in the specific context of project planning within IT and software project domains. A PRISMA-compliant systematic literature review was carried out. The utilization of PRISMA facilitated the identification, selection, and critical evaluation of research, thereby mitigating bias and enhancing the efficacy of the reporting process. Systematic literature reviews offer a means of observing and assessing the effectiveness of integrating AI in the planning phase of project management processes. As a result, this review may be useful in determining any knowledge gaps in this area. Moreover, it facilitates researchers' understanding of how AI is applied and advances knowledge of key ideas, investigative strategies, and experimental approaches in the project management domain.

3.1. The Search and Review Process

The review process was initiated by identifying keywords to structure a search for relevant scientific articles, utilizing the following boolean combination of keywords: ("project management" OR "plan*") AND ("artificial intelligence" OR "Machine Learning") AND ("challenge*" OR "limitation*" OR "barrier*") AND ("software development" OR "Information Technology"). This enabled a structured approach to locating relevant literature. Following the removal of duplication, the two authors of the current paper carefully read the selected papers that were chosen based on the eligibility criteria provided in Table 1. The following databases were selected for their extensive collection of academic papers: IEEE Xplore, ScienceDirect, Academic Search Premier, ACM Digital Library, and Emerald. A backward search methodology was also employed to review references within the identified articles to uncover further relevant studies. This systematic approach ensured that a comprehensive review aligned with the research was conducted. The selected databases

have distinct filtering options. In addition to the predetermined eligibility requirements, each database was individually navigated and filtered based on the specific criteria relevant to the focus of this study. This approach ensured that the search process was tailored to facilitate a comprehensive and precise selection of the literature. After applying all filters, the results for each database were as follows: Academic Search Premier (137 articles), ACM Digital Library (28), IEEE Xplorer (7 articles), Science Direct (316 articles), and Springer (861 articles).

Table 1. Inclusion and exclusion criteria.

Inclusion Criteria	Exclusion Criteria
peer-reviewed articles, reviewed conference papers	book review, magazine, reports, dissertation, theses, books, audio, video
language: English	non-English articles
limit year: 2019–2024	older than 2019
relevant to the application of artificial intelligence in project management	not relevant to the research question
papers available in full text within the selected databases	

3.2. Data Extraction

Details on various types of challenges, how to address them, and the features of the study methodology were extracted from the articles. The information collected for each study was concerned mainly with AI models used, and the limitations of integrating this technology in the planning phase of the project management process. Additionally, we have noted the research's findings and the authors' conclusions. Each related paper has been independently assessed by the authors to verify eligibility and retrieve answers to the research question. Any disagreements amongst the authors' perspectives were settled by conversation and consensus.

4. Results

Throughout each phase of the selection process, the study tracked and reported the number of studies identified, screened, and either included for further review or excluded, as shown in Figure 1 below.

Initially, a comprehensive search across five electronic databases provided 1264 articles. Of these, 201 were identified as duplicates and subsequently removed. A detailed review of titles and abstracts led to the exclusion of an additional 1022 articles, primarily because of their lack of direct relevance to the research question. This left 41 articles for an in-depth, full-text review. From this subset, 27 articles were excluded for reasons that included a focus on AI implementation in projects rather than on project management, discussions centered on learning software development, and articles addressing general project leadership without specific applications of AI. However, through a thorough backward search of references within the identified articles, we added three more studies, for a final count of 17 articles deemed suitable for qualitative synthesis (see Table 2). The identified articles with the models addressed in each article are listed in Table 3. The model is an algorithm that has been trained on a collection of data to find particular trends or come to conclusions on its own without the need for additional human input. Artificial intelligence models accomplish the tasks, or outputs, for which they are programmed by applying various algorithms to pertinent data inputs.
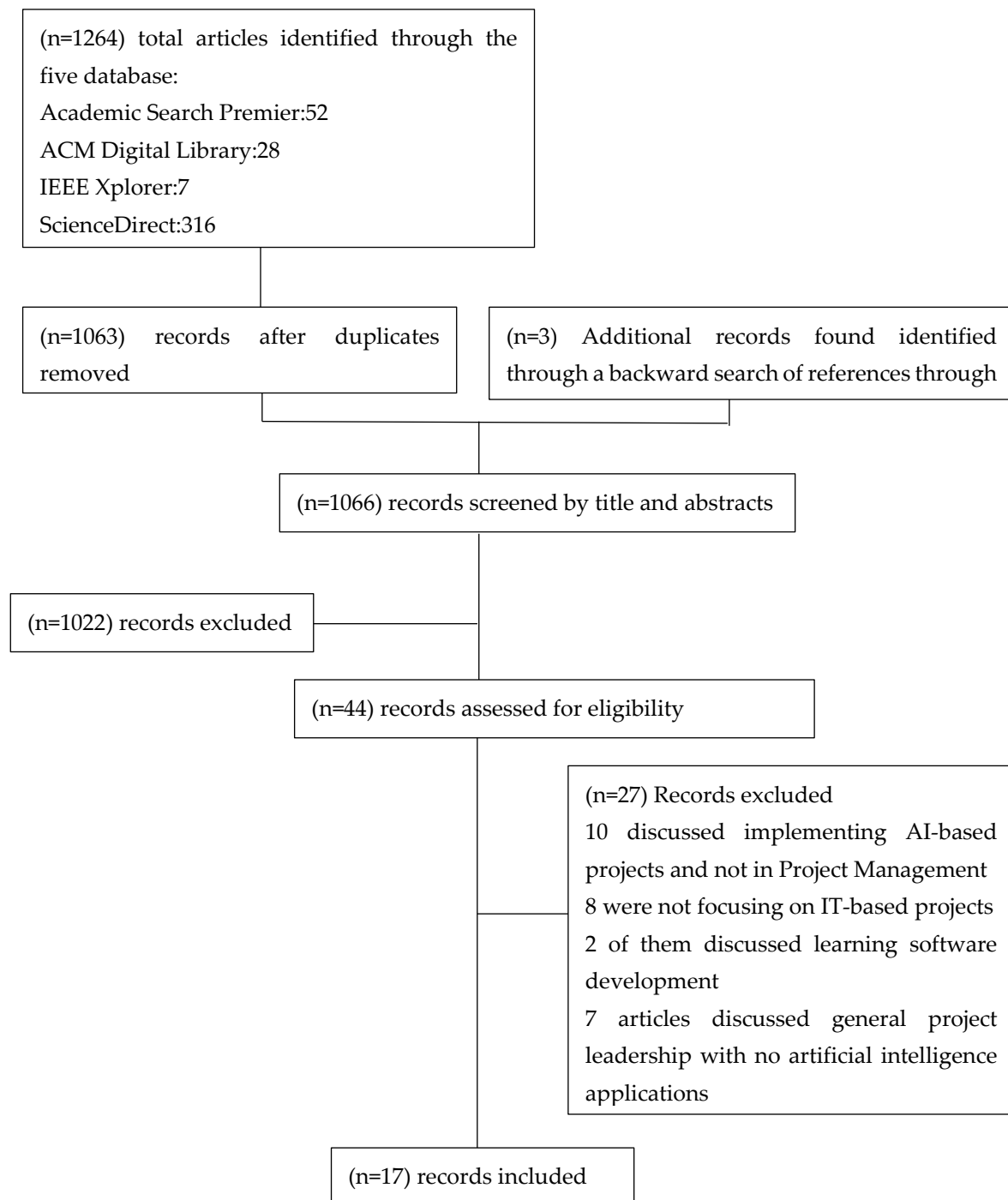
(n=1264) total articles identified through the five database:
Academic Search Premier:52
ACM Digital Library:28
IEEE Xplorer:7
ScienceDirect:316

(n=1063) records after duplicates removed

(n=3) Additional records found identified through a backward search of references through

(n=1066) records screened by title and abstracts

(n=1022) records excluded

(n=44) records assessed for eligibility

(n=27) Records excluded
10 discussed implementing AI-based projects and not in Project Management
8 were not focusing on IT-based projects
2 of them discussed learning software development
7 articles discussed general project leadership with no artificial intelligence applications

(n=17) records included

Figure 1. Flow diagram for the screening and selection of articles.

Table 2. List of selected articles and models addressed.

Article	Models Addressed
[7]	Support Vector Machine, Genetic Algorithm (GA), Ant Colony Optimization (ACO), Evolutionary Strategy (ES), Local Search (LS), Differential Evaluation (DE), and Practical Swarm Optimization (PSO)
[8]	Neural Network, Random Forest, and Support Vector Regression
[9]	Random Forest

Table 2. *Cont.*

Article	Models Addressed
[10]	Meta-heuristic algorithms: GWO, ZOA, MFO, PDO, and WSO
[11]	Decision Tree, K-Nearest Neighbor, Gradient Boosting, Neural Network, Naive Bayes, Support Vector Machine, and Bayesian Network
[12]	Genetic Algorithm (GA)
[13]	Vector machine, K-Nearest Neighbor, Artificial Neural Network, and Random Forest
[14]	SVM, MLP, decision trees, and Random Forest
[15]	Classification model
[16]	Smart AI assistant, conversational AI platform (LLMs)
[17]	Gradient Boosting, Neural Network,
[4]	word2vec, paragraph2vec, Long Short-Term Memory (LSTM), and Convolutional Neural Networks (CNNs)
[18]	Decision Tree, K-Nearest Neighbor
[3]	Naive Bayes
[19]	ChatGPT GPT-4o
[5]	Support Vector Machine, and Bayesian Network
[20]	GPT-2 language models and Transformer architecture

Table 3. AI models addressed and the number of covered papers.

AI model Group	Number of Papers	Models Included
Neural Network	11	(Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM), Smart AI assistant, conversational AI platform, ChatGPT GPT-4o (GPT-4), GPT-2 language models, Transformer architecture)
Support Vector Machine	5	(Support Vector Machine, Support Vector Regression)
Random Forest	4	Random Forest
Genetic Algorithm	2	Genetic Algorithm
Decision Trees	2	Decision Tree
K-Nearest Neighbor	2	K-Nearest Neighbor
Other Models	17	Ant Colony Optimization (ACO), Bayesian Network, Case-Based Reasoning (CBR), Classification model, Differential Evaluation (DE), Evolutionary Strategy (ES), GWO, Gradient Boosting, Local Search (LS), MFO, Naive Bayes, PDO, Practical Swarm Optimization (PSO), WSO, ZOA, paragraph2vec, word2vec

4.1. Characteristics of Research Articles

It is observed in this study that there has been increased interest in applying AI in project planning from 2021 to 2023, as shown below. The highest number of articles was published in 2023 (55%) (see Figure 2), while 27% were published in 2022.

The 17 selected articles highlighted different challenges. As mentioned above, this study categorized the challenges using the TOE framework. Table 4 below showcases how these challenges were divided into sub-themes and what articles referenced them.

Table 4. TOE challenges summary—distribution across articles.

| Context	Challenges	Refs.
Technological	Data Availability and Quality	[7,9–12,14,18]
	Model Adaptability and Advancement	[4,7,9–11,14,19,20]
	Resources Limitations	[5,12,14,18]
	Integration into Existing Project Management	[3,7,12,13,19,20]
	Technical Expertise	[3,5,11,16,19]
Organizational	Transparency and Accountability	[8,14,19,20]
	Change Management	[7,16]
	Generalizability Across Ecosystems	[8,11,12]
Environmental	Project Dynamics	[3,15,16]
	AI Ethics and Regulations	[17]
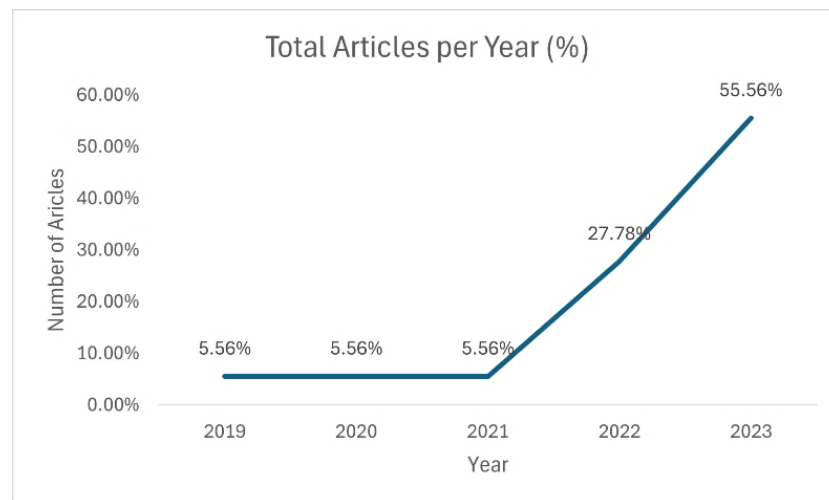
Figure 2. Distribution of articles per year.

4.2. Technological Challenges

Technological factors within the TOE framework refer to the technological limitations that affect the implementation of the AI models. This includes assessing the capabilities of adopting the AI models in project planning. Understanding these factors is crucial for organizations considering new technologies [6]. Therefore, this review classified data availability and quality, model adaptability and advancement, and resource limitations as falling into the technological group (see Table 4).

4.2.1. Data Availability and Quality

This section critically reviews articles discussing data availability and quality limitations for AI models in project planning. Seven of the selected articles explore this type of limitation (see Table 4).

Ref. [17] conducted a systematic literature review on software project scheduling using AI and highlighted the constraints presented by the use of synthetic datasets, which, while useful, may not accurately translate to real-world scenarios where variables are more dynamic and complex. However, this potentially leads to inaccuracies in task assignments and schedule predictions. This concern is echoed by [9] who scrutinized the Random Forest Model's training data and identified significant issues with missing information within the libraries.io dataset. The gaps, particularly in repository links, pose a serious question regarding the model's ability to accurately reflect the current practices and trends in the Node Package Manager 10.8.1 (npm) ecosystem, given the dataset's exclusion of data beyond January 2020.

Furthermore, to support the concerns raised by [7,11,12] cited limitations in AI predictive capabilities owing to the availability and reliability of historical data. In this context, ref. [11] observed that the historical data and variables typically utilized to train AI models might not contain the particularities of innovative and complex projects, while [12] emphasized the significant dependence of the Case-Based Reasoning with Genetic Algorithm (CBR-GA) model's accuracy on high-quality historical project data, noting that any inaccuracies or biases present in the historical datasets could substantially affect the model's functionality.

Additionally, ref. [14] reviewed different machine learning algorithms for estimating software development efforts, introduced a different dimension to the discussion by highlighting the challenges associated with the dataset size. They outlined how larger datasets could introduce over-generalization issues, potentially leading to models that do not adequately capture specific and detailed project needs. Conversely, smaller datasets might result in overfitting, where models are too closely tailored to the training data and fail to generalize to new data. However, this observation adds a layer of complexity to the

dataset management challenge, revealing that the dataset's size, breadth, and depth are as critical as the quality and completeness of the data itself.

Addressing the methodological considerations of the dataset used in AI model training, ref. [10] also studied improving software effort estimation using machine learning, indicated the potential benefits of expanding the sample size to obtain a broader and more representative set of data, which could enhance the validity of the research findings. In agreement with this suggestion, ref. [18] proposed standardizing process modeling and articulating clear risks to avoid issues that might affect the efficiency of applications and the success of machine learning models, such as pattern overfitting, accuracy degradation, and the threat of overfitting owing to model misadjustments.

In contrast to the discussions on data limitations, ref. [7] also touched upon the adaptive capabilities of dynamic models, suggesting that they may address the uncertainties and variations in project scheduling, thus dealing with real-world complexities more effectively. Real datasets can significantly enhance the efficiency of task scheduling, providing models with precise tangible data for training and validation purposes.

However, ref. [12] advocate studying reference studies that evaluate methods for addressing historical data gaps to resolve the challenges related to missing and incomplete data. They highlighted techniques such as deletion and imputation methods, with the latter being shown to significantly improve the accuracy of analogy-based effort estimation models. Such an approach underscores the importance of addressing data shortcomings to ensure the success and reliability of predictive models such as Case Base Reasoning with Genetic Algorithm (CBR-GA).

4.2.2. Model Adaptability and Advancement

Ref. [11] stated the limitations of static models in adapting to evolving project landscapes, emphasizing their static nature as a barrier in dynamic environments. Concurrently, [9] uncovered difficulties in accurately predicting restrictive update strategies using their model, demonstrating high precision and low recall. However, this reflects not only the model's capability to identify restrictive packages accurately but also its failure to detect many such instances, a limitation linked to the dataset's minor focus on restrictive strategies, and the contingent nature of these strategies on external factors, such as breaking changes, rather than intrinsic package characteristics.

Also, in their exploration of enhancing software estimation models, ref. [10] pointed out a critical oversight: the estimation process overlooked the complexity of software systems, treating them as monolithic entities rather than compositions of diverse subsystems. This simplification potentially hampers the precision and relevance of the model to real-world applications. By contrast, ref. [20] introduced the advantages of applying the attention mechanism in transformer-based models for agile story point estimation, marking a novel approach that improves interpretability and accuracy by illuminating the rationale behind model predictions.

Additionally, ref. [19] critiqued the generative capabilities of AI systems, such as ChatGPT GPT-4o, noting their tendency to provide singular responses to prompts rather than exploring the breadth of possible outputs. This limitation could restrict the comprehensiveness of project planning as the multitude of potential outcomes and their implications remain unexplored. However, ref. [7] also highlighted the integration of machine learning algorithms, such as Support Vector Machine (SVM), with task scheduling and strategies to augment task assignments' accuracy and efficacy.

However, ref. [11] advocated additional testing with enriched datasets to better understand the dynamics between relevant variables, thereby enhancing model performance. This suggests a constructive pathway for overcoming these limitations. Moreover, ref. [14] proposed developing a hybrid model that combines the strengths of various machine learning techniques to boost estimation accuracy. This innovative approach can significantly refine software effort estimation by optimizing default algorithmic parameters. In support, ref. [4] introduced the concept of employing deep reinforcement learning to forge a segment

of the planning engine that is adaptable and predictive of potential sprint execution barriers, aiming for a robust and resilient planning process.

4.2.3. Resources Limitations

Ref. [12] underlined the complexity and resource-intensive nature of the CBR-GA model's optimization process, necessitating considerable computational power and time for tasks like feature selection and determining the optimal number of nearest neighbors. This complexity poses a significant challenge for resource-limited settings. Similarly, ref. [14] shed light on the computational hurdles and scalability issues faced when handling large datasets, worsened by the problems of dimensionality, noise, and outliers, impacting the precision of software effort estimations.

Additionally, ref. [5] discussed the substantial initial investments in hardware and software infrastructure required for AI technology deployment, a formidable obstacle for many organizations. In contrast, ref. [18] provided a solution by advocating the strategic selection of cloud services, edge computing devices based on specific computational needs, and user-friendly reporting tools, including smartphone-compatible dashboards, to mitigate these barriers.

Furthermore, ref. [18] addressed the operational challenges of maintaining and updating machine learning models to preserve their accuracy and relevance over time. The continuous evolution of ML models requires regular performance monitoring, model updates, and parameter tuning. To address these issues, they proposed adhering to the Cross-Industry Standard Process for Machine Learning (CRISP-ML) methodology, employing Machine Learning Model Operationalization Management (MLOps) practices, utilizing Predictive Model Markup Language (PMML) for efficient model tracking and archiving, and integrating CI/CD pipelines to streamline model deployment and use. This comprehensive approach underscores the importance of strategic management and operational efficiency in effectively leveraging AI and machine learning technologies in information technology projects.

4.3. Organizational Challenges

The obstacles arising from the internal operations of the organizations managing the software project are referred to as organizational barriers. Therefore, the organizational challenges must be considered concerning the organization's intention to use AI technology as part of its project management methodology. This review revealed four organizational obstacles to the integration of AI in project management: integration into existing project management, technical expertise, transparency and accountability, and change management.

4.3.1. Integration into Existing Project Management

Integrating artificial intelligence (AI) models into existing project management and planning frameworks presents complexities that can obstruct seamless adoption, as noted by [7]. This challenge is further compounded in the context of agile development methodologies, where the conventional design of models such as CBR-GA may not align well with agile's dynamic nature and reliance on metrics such as story points, according to [12] However, advancements such as the Transformer-based Agile Story Point Estimation (GPT2SP) approach, leveraging the GPT-2 architecture, have shown promise in accurately estimating story points in agile environments, as ref. [20] have demonstrated. This tool enhances the accuracy of estimations and the interpretability of decision-making processes by highlighting influential keywords and providing relevant historical examples.

Additionally, ref. [19] revealed that AI-driven and human-crafted project plans possess distinct advantages and limitations, suggesting that a synergistic approach could provide efficiency and depth of project planning. This perspective advocates integrating human expertise with AI-generated insights to elevate the quality and thoroughness of the project plans. Moreover, the rise in the adoption of scrum methodologies in software projects

has highlighted the absence of risk management practices within such frameworks, a gap highlighted by [13]. This omission underscores a critical challenge in effectively foreseeing and mitigating project risks using AI models for risk prediction. However, Gouthaman and Sankaranarayanan proposed incorporating risk management into agile methodologies through a continuous feedback loop to strengthen the success rates of agile projects by fortifying risk-management practices.

To address the operational challenges of AI in agile project management, ref. [4] explained the complexities of formulating the AI planning problem. The complex process requires defining the initial state, which includes the project status before a sprint and the objectives of the sprint as the goal state. The multifaceted decision-making involved in transitioning from the initial to the goal state is compounded by the need to account for various inputs, such as product backlog items, team capacity, and previous sprint performances. The transformation of these often informally expressed factors into vector representations for AI planning necessitates advanced representation learning engines and formal encoding.

4.3.2. Technical Expertise

Ref. [11] underscored the challenges that arises from the intricate nature of some AI models, particularly those built on sophisticated algorithms, which can be opaque and difficult for project managers without deep technical knowledge to interpret them. This opacity complicates the application of AI in informed project management decisions because of the inability to understand the basis of the model's forecasts.

Ref. [3] also acknowledge AI's potential to boost project outcomes, especially in the information technology (IT) domain. However, they emphasize the undiminished need for adept project managers capable of leveraging their expertise to incorporate AI tools effectively into project workflows. Ref. [5] pointed out the specialized skills and experience required to develop, deploy, and maintain AI systems within project planning, noting the recruitment and retention of such skilled personnel as a significant challenge. Addressing the training gap, ref. [16] recommended the adoption of AI-powered tutoring systems endowed with natural language processing abilities to facilitate training. These systems enable interactive, conversational learning sessions, thereby democratizing access to training for customers and staff at their convenience.

Additionally, ref. [19] introduced the concept of prompt engineering, a skill learned by project managers. This novel skill involves the strategic formulation of inputs to steer AI towards generating outputs more aligned with project-specific requirements. In addition, this skill is pivotal for optimizing the utility of AI in project planning, enabling the tailoring and enhancement of AI-generated proposals to suit the unique demands and limitations of projects.

Furthermore, ref. [5] raised concerns regarding the potential for AI systems to displace human jobs, suggesting the risk of increased unemployment as AI assumes roles traditionally filled by humans. However, ref. [3] argued that domains reliant on human intellect and interpersonal skills, such as team development and stakeholder management, are likely to remain less impacted by AI. This viewpoint recognizes AI's limitations in fully replicating human cognitive and social interactions.

Moreover, ref. [19] acknowledged the capabilities of AI in generating components of project plans but stressed the indispensable role of human project managers. Their expertise is crucial for refining AI-generated outputs, ensuring plans are realistically executable and closely aligned with overarching project objectives. This collaboration between human expertise and AI innovation is essential for realizing the full spectrum of benefits that AI offers to project planning, underlining the symbiotic relationship between technology and human insight in navigating the complexities of project management.

4.3.3. Transparency and Accountability

In their investigation into employing AI to estimate the functional size of software, ref. [8] drew attention to the inherent "black-box nature" of many machine learning algorithms. This characteristic complicates the documentation, tracing, and elucidation of the processes, results, and logic underpinning machine learning algorithms, rendering them less transparent and difficult to interpret. Such opacity becomes a critical issue in scenarios demanding clear and accountable decision-making, notably within the public sector, where outcomes shrouded in ambiguity and lack of reliability can hinder stakeholder acceptance and trust. Despite these challenges, ref. [19] suggested that harmonizing human insight with AI in project planning can forge more credible and effective project plans. By blending human expertise with AI's analytical process of AI, project planning can achieve greater efficiency, innovation, and effectiveness.

Additionally, ref. [20] revealed that AI-driven story-point estimations, when accompanied by explanations, are deemed more valuable and trustworthy by users than those without justification. Furthermore, a significant number of survey participants (69%) expressed a willingness to adopt AI-enhanced agile story-point estimates, especially if these systems were integrated into widely used software development platforms such as JIRA. This finding underscores the industry's growing recognition of and potential readiness to embrace explainable AI solutions for story-point estimation.

Ref. [14] pointed out another dimension of complexity in the real-world application of AI models, emphasizing the influence of situational factors and company-specific standards, such as the Capability Maturity Model (CMM) levels. These variables can significantly impact the effectiveness and suitability of AI solutions across different organizational contexts, underscoring the need for adaptable and flexible AI applications tailored to meet diverse operational standards and project environments.

4.3.4. Change Management

Ref. [16] highlighted an implicit challenge in ensuring that all team members find AI tools neither too hard nor too easy to use. This indicates a need for training or an adaptation period for employees to become accustomed to new software and tools. Ref. [7] also note that adopting AI models in planning involves significant changes in processes and workflows. Therefore, organizations may encounter resistance from employees who are accustomed to traditional methods. Thus, effective change management strategies are essential to address these concerns.

4.4. Environmental Challenges

This review discusses three important environmental challenges that affect the use of AI in project management planning, as follows: generalizability across ecosystems, project dynamics, and AI ethics and regulations.

4.4.1. Generalizability across Ecosystems

Ref. [8] pointed out that their findings and the model's efficiency are confined to the npm ecosystem. This suggests that its applicability might not extend seamlessly across various software ecosystems, each characterized by its practices, cultural norms, and dependency management techniques. Nonetheless, they proposed that the study's methodology and approach could be applied in other ecosystems with similar types of dependency data.

Ref. [11] pointed out the inherent complexity in using AI models to select the most fitting project management methodology, primarily due to the diversity of projects that lack a universal solution. They emphasize the critical need for a detailed evaluation of each project's specific characteristics, context, and setting, and a step frequently bypassed in favor of intuitive or discriminatory decisions. Such oversight can profoundly affect the project outcomes. Furthermore, the study acknowledges that AI models, including those based on machine learning, are trained on historical project data, which may hinder

their ability to generalize effectively to projects with distinct or unprecedented features absent from the training data, thus affecting the precision of identifying the optimal project management approach for these cases.

Similarly, ref. [12] highlighted variations in model performance across different datasets, noting that although the model demonstrates an improvement in accuracy compared to traditional CBR methods, its efficacy may diminish with smaller datasets. This variation indicates a potential challenge in the model's capacity to generalize across diverse software project datasets, suggesting that its utility might be constrained in specific scenarios.

4.4.2. Project Dynamics

Ref. [15] highlighted a significant challenge in the task-planning model used for software process planning, the prerequisite for early and precise estimations of the project's size and timeline. Given the fluid nature of software development projects, where requirements and scopes are subject to change, this model's rigidity in needing upfront estimations is a notable drawback.

Additionally, ref. [3] emphasized the critical need for developing all-inclusive frameworks for AI-enhanced project management that cover various project life cycle performance domains, including sustainability and security, and facilitate project managers' adoption. They underlined the research gap in these essential areas, which are pivotal for seamlessly integrating AI into project management routines.

Similarly, ref. [16] observed the frequent introduction of additional requirements by clients in the final stages of a project, which complicates the project management process by necessitating adjustments to the project timeline and reallocating resources. They also highlight client availability and engagement challenges, such as missing meetings or unavailability for crucial decisions. However, they suggested implementing intelligent AI assistants to schedule regular meetings and automate the preliminary collection of client information. This strategy includes ensuring the availability of at least one decision-maker to prevent delays, streamlining the project management process, and enhancing efficiency despite potential hurdles.

4.4.3. AI Ethics and Regulations

Ref. [17] identified a notable gap between AI ethics guidelines and industrial practice, particularly in societal and environmental well-being, diversity, nondiscrimination, and fairness, which are not adequately addressed. In addition, companies largely ignore the societal and ecological well-being requirements of software development [21,22]. However, they suggested using methods or tools for implementing AI ethics as a practical implication of their findings. One such method is ECCOLA, which can address identified gaps by providing a structured approach to ethical considerations in AI development.

5. Discussion

This review examined AI models in IT project planning and unveiled a series of challenges classified within technological, organizational, and environmental domains [6]. This discussion delineates these challenges, leveraging insights from the literature to propose future research directions and practical applications. According to this review, technological and organizational challenges received more attention than environmental challenges. This review showed that eleven articles reported technological challenges, twelve articles identified organizational challenges, and six articles reported environmental challenges (see Figure 3). This is due to the technological novelty of AI technology in the field of project management. However, this also reflects a research gap, in terms of environmental barriers that might have a negative impact on the success of the integration of AI in project planning. According to the Project Management Institute [1], a project is "a temporary endeavor undertaken to create a unique product, service or result". In this context, the uniqueness of a project's environmental factors makes it difficult to generalize AI solutions to different projects, especially when the project's distinct or unprecedented

characteristics were absent from the training data, thus affecting the precision of project management planning such as resource, cost, and schedule planning. Therefore, further research on this perspective is needed.
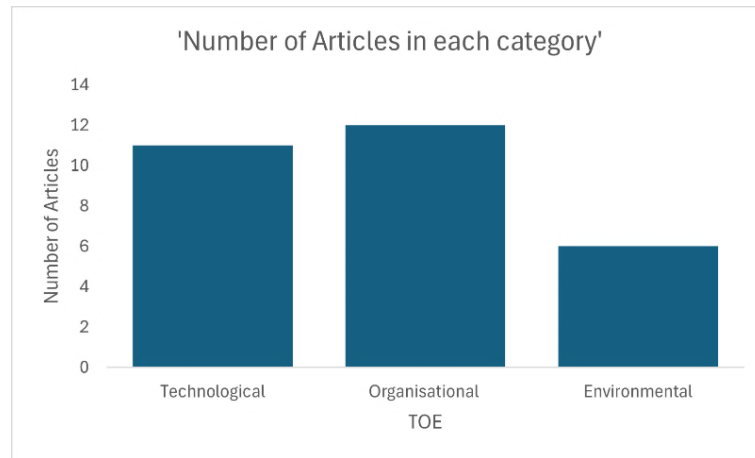

Figure 3. Number of articles per TOE category.

Another category of challenges reported by the selected articles were the technological obstacles that primarily concern data availability and quality, model adaptability and advancement, and resource limitations (see Figure 4). In this regard, this review showed that seven of the selected articles reported the challenge of data availability and quality, revealing issues from different angles such as the reliance on synthetic datasets, missing data, and the inadequacy of historical data for training AI models [7,9,11]. However, this review also showed that the literature neglected the confidentiality and integrity of the sensitive data collected and input into the machine language models, especially since these data exists in most projects if not all of them. This means ignorance of the two essential pillars of the information security triad. As a result, the privacy of the data is compromised, which also represents neglecting to adhere to data protection regulations and laws such as the General Data Protection Regulation (GDPR) and The California Consumer Privacy Act (CCPA). In this regard, this review showed that there is no article has discussed this issue. Therefore, to fill this gap, further research on this topic is needed.
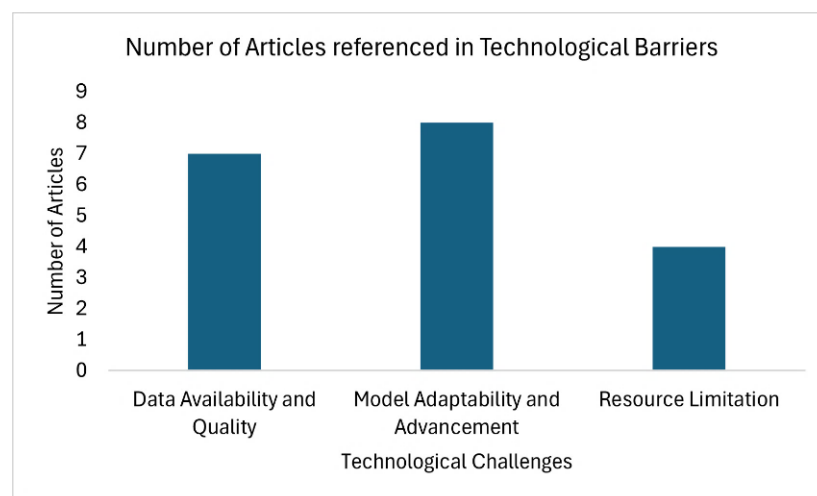

Figure 4. Number of articles in each technological challenge identified.

Additionally, this review revealed that eight of the selected articles reported the limitations of the static models and the need for models that can adapt to evolving project landscapes [7,9,11]. Thus, there is still a gap in exploring the development of dynamic, self-evolving AI models, which was only addressed by two papers [7,9] exploring models that need to be continuously updated based on new project data and interactions, providing a pathway to overcome these limitations. Furthermore, this review showed that four articles pointed out the computational and resource barriers to AI model development and deployment. In this context, it is clear that the literature lacks an in-depth analysis of computational resources like cloud computing and algorithmic efficiencies that could mitigate these constraints.

Additionally, this review showed that six articles illustrated the complexities of integrating AI within traditional project management frameworks (see Figure 5). In this regard, the need for specialized skills for AI deployment, which was reported in five articles, was considered a substantial challenge. However, there is also a notable gap in strategies for upskilling project management professionals and the role of AI-powered tutoring systems in democratizing access to training. Furthermore, this review showed that four articles raised concerns about AI's lack of transparency and the need for explainability in AI-driven project management decisions. This issue becomes critical in scenarios requiring transparent and accountable decision-making, particularly within the public sector, where outcomes wrapped in ambiguity and lack of reliability can impede stakeholder acceptance and trust. Finally, change management is one of the challenges that has not received much attention in the selected articles; only two articles emphasized this barrier. It is, therefore, necessary to further research this area.
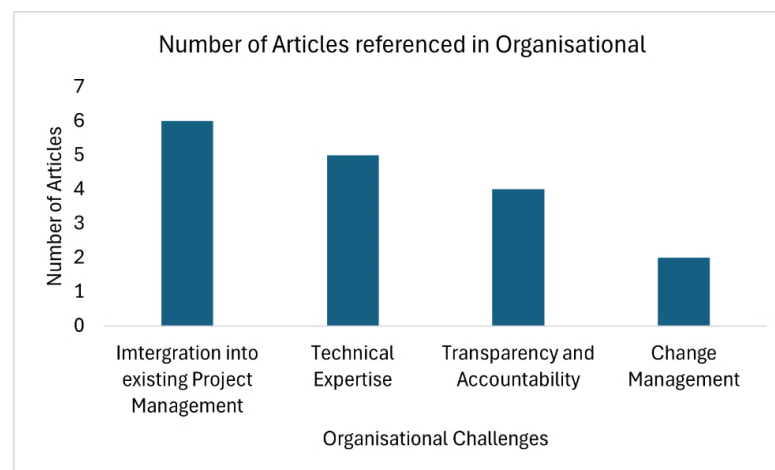

Figure 5. The number of articles in each organizational challenge identified.

Furthermore, this review showed that the applicability of AI models across various software ecosystems is a significant concern (see Figure 6). As reported in three articles, this is due to the rigidity of AI models in accommodating the fluid nature of project requirements and timelines. Furthermore, this review showed that the discrepancy between AI ethics guidelines and their application in practice is one of the key challenges, as reported by [17], who indicated the need for structured approaches to ethical AI development. This point is in line with the previously discussed argument about the importance of compliance with data protection regulations and laws.
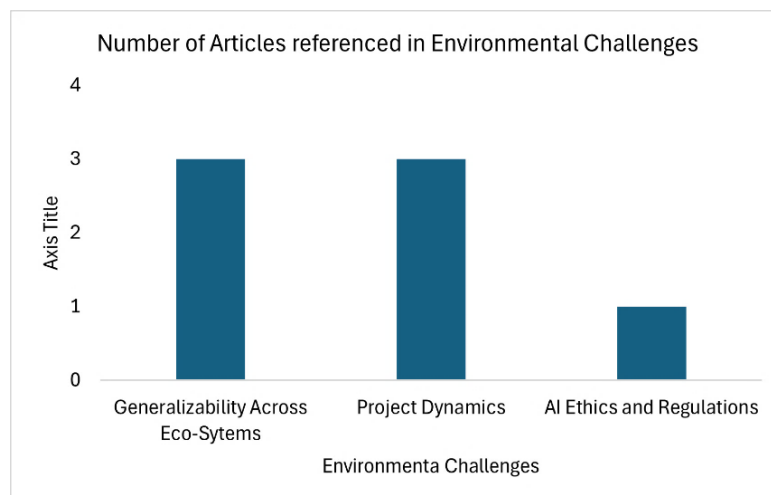
Figure 6. Number of articles in each environmental challenge identified.

6. Challenges and Future Directions

The study only focused on five databases (IEEE Xplore, ScienceDirect, Academic Search Premier, ACM Digital Library, and Emerald); as a result, relevant articles in other scientific databases might have been overlooked. In addition, the study is limited to the models listed in Table 3. Hence, developing new models or models that are not addressed might present challenges. Furthermore, the study restricted the number of irrelevant papers based on eligible criteria (i.e., those that were published a long time ago, were overly generic, or did not specifically address the research issue). Moreover, only English-language items were included; as a result, relevant articles written in languages other than English may have been excluded by these criteria. These limitations might have affected the retrieval of important records and had an impact on the number of records collected. Consequently, the number of articles investigated and the relevance of different research papers limited our research. They might have had an impact on our data extraction and analysis as well. These limitations, however, had no appreciable effect on the discussion and conclusions.

This study can guide future researchers in this area with a focus on environmental challenges, especially how region regulations, i.e., GDPR, will affect the implementation of the AI models in project planning as they have been underexplored. Additionally, a focus on data handling and privacy should also be explored.

7. Conclusions

The future of artificial intelligence (AI) in the project management field is very promising. Therefore, the key contribution of this review was to identify the challenges of implementing AI in the project planning phase, particularly within IT and software projects. This review answered the research question "What are the challenges of Artificial Intelligence in project planning for IT/Software Projects?" by identifying and categorizing these challenges according to the Technology–Organization–Environment (TOE) framework. The technological barriers are as follows: data availability and quality, model adaptability and advancement, and resource limitations. In the organizational context, there is integration into existing project management, technical expertise, transparency and accountability, and change management. In the environmental context, there is generalizability across ecosystems, project dynamics, and AI ethics and regulations.

This review showed that environmental challenges received less attention from the reviewed articles than the other two contexts. This reflects a research gap in terms of environmental challenges. This will have a negative impact on the success of the integration of AI in software project planning. Therefore, more research is needed from this perspective, especially the effect of applying regional regulations like the GDPR. This review also

showed how the confidentiality and integrity of sensitive data gathered and input into machine language models were overlooked in the literature, particularly given that these data are included in the majority of projects, if not all of them. Furthermore, this review disclosed that the inconsistency between AI ethics guidelines and their use in practice is one of the key challenges.

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