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Implementations of Artificial Intelligence in Various Domains of IT Governance: A Systematic Literature Review

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Abstract

Background: Artificial intelligence (AI) has become increasingly prevalent in various industries, including IT governance. By integrating AI into the governance environment, organizations can benefit from the consolidation of frameworks and best practices. However, the adoption of AI across different stages of the governance process is unevenly distributed.
Objective: The primary objective of this study is to perform a systematic literature review on applying artificial intelligence (AI) in IT governance processes, explicitly focusing on the Deming cycle. This study overlooks the specific details of the AI methods used in the various stages of IT governance processes.
Methods: The search approach acquires relevant papers from Elsevier, Emerald, Google Scholar, Springer, and IEEE Xplore. The obtained results were then filtered using predefined inclusion and exclusion criteria to ensure the selection of relevant studies.
Results: The search yielded 359 papers. Following our inclusion and exclusion criteria, we pinpointed 42 primary studies that discuss how AI is implemented in every domain of IT Governance related to the Deming cycle.
Conclusion: We found that AI implementation is more dominant in the plan, do, and check stages of the Deming cycle, with a particular emphasis on domains such as risk management, strategy alignment, and performance measurement since most AI applications are not able to perform well in different contexts as well as the other usage driven by its unique capabilities.

Keywords: Artificial Intelligence, Deming cycle, Governance, IT Governance domain, Systematic literature review

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I. INTRODUCTION

Artificial intelligence (AI) is rapidly advancing and making its way into various business domains, involving government law and policy-making, public healthcare, information, communication, and technology (ICT), environmental sustainability, transportation, economics and finance, and more[1], [2]. AI comes with numerous benefits, including making decisions more effectively than humans when judgment is not necessary, ease of implementation, rapid return on investment, and use as the foundation for the cognitive potential of innovative products and services [3]. AI has facilitated the development of methods and tools for managing computer-based knowledge and techniques for knowledge-based reasoning and analytical thinking. These include knowledge modeling and acquisition, analytical reasoning, machine learning, multi-agent systems, natural language processing, and analogical reasoning [4].

The age of AI technology is about 60 years old, and its existence has provided various technology that has a massive impact on our lives [5]. One of the milestones considered significant in the development of AI is the Turing Machine in 1937, introduced by Alan Turing. This ideal intelligent computer model was developed based on automata theory. The innovation inspired other researchers to create a "thinking machine" to emulate human thought processes [6].

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AI research has gone through three stages. In the initial stage, AI introduces the concept with limited processing due to computing limitations. In the second, AI focused on neural networks, mimicking human thinking, showing potential for cognitive processes. In the current third stage, AI is integrated into real-world problem-solving using deep learning [7]. While it has advanced, there are certain areas or domains in which AI is still considered new.

The application of AI to IT Governance has enormous potential to improve management performance and reduce costs. However, this also raises challenges that must be overcome and managed effectively [4]. Surprisingly, most companies that already implement AI in their business strategy priorities report only 11% significant financial benefit [8]. The IT department's governance structure is often the weakest aspect of a company. Business management is paying much more attention to IT governance, one of the key functional governance models [9].

In previous research, there have been many literature reviews regarding AI and IT governance. The use of AI in various government sectors has been reviewed in [2] to develop a framework that outlines the area of governance in general. This research did not explicitly focus on the ICT sector or discuss the specific implementation of AI in IT governance. The study in [9] reviewed existing IT governance research and introduced a framework to structure previous findings. The author of this study categorizes research on IT governance into two distinct streams of progress and finds that academics and practitioners are still exploring IT governance to discover effective ways of managing corporate IT decisions. This research neglected the aspect of implementing AI for IT governance. The study in [10] reviewed and categorized a lot of studies in the strategic management field. It also introduced a framework that organizes existing concepts. This study concludes that AI has the potential to significantly impact an organization’s strategic management. This study focused on the application of AI in strategy management as part of the governance process. However, these previous studies did not review the implementation of AI in the processes of IT governance.

In IT governance, the Deming cycle is a well-known model used to maintain process quality [11]. This model consists of 4 stages: plan, do, check, and act. The application of AI to IT governance can be carried out at one or several of these stages. This study aims to give a thorough overview of how AI is used in IT governance processes based on the Deming cycle through a systematic literature review. It also contributes to investigating AI's potential in IT Governance, identifying research gaps, and offering insights and recommendations for organizations considering AI adoption in their IT governance.

The rest of the paper is organized as follows. Section 2 describes the literature review. Section 3 provides an explanation of the method. Section 4 describes the results. Section 5 discusses analysis and provisions for future work. Finally, Section 6 presents our conclusions.

II. Literature Review

A. Deming Cycle

The Deming cycle or the Deming wheel, Plan-Do-Check-Act (PDCA) model, or Shewhart cycle, is a well-known quality management method [11]. This model consists of four steps. Plan, is a step to defining the activities for the goal realization. Do, is an action to implement the plan. Check, is a step to monitoring and evaluating the result. Act, is an effort to improve the processes and search for new ideas for the next cycle [12].

B. IT Governance

IT governance is a system of relationships and procedures that helps businesses manage their operations so they may add value to their operations while balancing their risk [13]. Five domains in IT governance have achieved worldwide recognition because business needs to drive them and are in sync with the board and executive management's priorities. These domains encompass IT strategic alignment, IT resource optimization, risk management, IT value delivery, and performance measurement. IT strategic alignment aims to ensure a strong connection between business and IT governance to deliver value. IT resource management focuses on maximizing knowledge and infrastructure. Risk management involves discussions about risk awareness and the organization's capability to manage risks. Performance measurement is all about tracking and overseeing project progress, performance, resource allocation, and service delivery. IT value delivery executes value throughout the cycle [14], [15].

C. Artificial Intelligence

Artificial Intelligence (AI) is designed to replicate human intelligence by imitating human thought processes. This technology employs data as a source of knowledge, enabling artificial intelligence to learn from previous mistakes and improve over time [16]. Artificial intelligence can be activated by human commands or autonomously based on prior experiences. Additionally, AI can self-repair since it was programmed to learn from previous mistakes [17]. AI can perform any of the four tasks: simulating human behavior, imitating human thought processes, employing rational thinking, and using rational behavior [10].

D. Related Secondary Studies

Secondary research has been conducted to investigate the potential applications of AI. These individual studies were carried out independently, each addressing distinct issues, as indicated in Table 1.

Sharma et al. [2] found a need for further research connecting AI with governance. The objective of this research is to offer a comprehensive overview of the potential applications of AI across different government sectors. This study has created a framework that provides a general overview of governance without specific emphasis on the ICT sector or a detailed examination of AI's implementation in IT governance.

Chakir et al. [4] developed an intelligent IT-GRC platform, enabling IT managers to customize their own repository while taking into account the effectiveness of each best practice, the organization's specific context, and the IT strategic requirements expressed by their stakeholders. This study focuses on the efficacy of using various IT governance standards and best practices within organizations rather than on the stages or processes of IT governance.

Keding C. [10] discovered that AI is a challenging but quick solution. Many organizations struggle to implement AI due to their structures and the need for effective employee collaboration. AI assists managers in automating routine tasks, allowing them to focus on more meaningful work and cope with large volumes of data while overcoming cognitive limitations. This study centered on utilizing AI in strategic management within the governance processes.

Alet J. [18] investigated how AI can be implemented and integrated with a company’s business strategy. This study aims to discover factors and potential to maximize AI's ability effectively in developing business strategies.

Al-Sartawi A. [7] explained how AI could support IT governance by proposing an IT governance model in three layers: structure and process, enterprise governance of IT, and relational mechanism. However, the researcher observed that the topic of how AI can be applied within various sectors is limited, as it has its own risks involved when using AI, even though AI can positively impact IT governance. This study aims to discover the appropriate IT governance model so that AI can be utilized optimally.

Dafoe A. [19] defines AI governance as the collective efforts to understand the technical aspects of AI, navigate the political dynamics surrounding its use, and envision ideal structures for the transition to advanced artificial intelligenceThis study categorizes the subject into three groups: the technical aspect, AI-related policies, and exemplar governance in AI, emphasizing the importance of holistic strategies to tackle the ethical, legal, and societal consequences of AI.

Previous studies indicate that AI can be utilized to support the implementation of AI governance. Organizations can employ AI to determine IT governance standards/best practices [4] and develop an appropriate business strategy [10], [18]. Previous studies have also reviewed frameworks and models for IT governance that AI can effectively support [7], [19], including in the government sector [2]. However, there have yet to be any previous studies that have addressed how the implementation of AI in IT governance processes, especially within the Deming cycle, which is essential for continuous improvement.

TABLE 1
RELATED SECONDARY STUDIES

Reference	Goal	Concern with the research question
[2]	Investigate how AI can be applied in different government sectors, including healthcare, the public, and more.	Overview of AI applications in diverse government sectors.
[4]	Develop an AI-based platform to help IT managers design repositories to assist in risk compliance in IT governance.	Overview of how to integrate updates of the knowledge base IT platform
[10]	Organize and integrate ideas from four decades of research to identify promising research prospects in the intersection of AI and strategic management.	Overview of how AI is implemented in four decades of research
[18]	Investigate factors and potential to maximize AI effectively	Overview of how to implement AI effectively by some factors and potential
[7]	Examine the Artificial Intelligence (AI) and IT governance roles of one another.	Overview of how AI Influences IT governance
[19]	Define AI governance, and it’s essential for the future research of AI.	Overview of how AI governance nowadays

III. METHODS

We adopted procedures from [20]–[22] in preparing this study. The processes include review planning and conducting the review.

A. Review Planning

We created a review plan by deciding which research topics were pertinent to the goal. We chose a search method and developed specific inclusion and exclusion criteria.

1) Goals and Research Queries

As previously noted, there needs to be more research that links the implementation of AI with IT governance processes associated with the Deming cycle. To fill this gap, we set the research question that we want to answer with this review: *"How are the applications of AI in each domain of IT Governance, especially with regard to the Deming cycle?"*

2) Search Query

We identified keywords, created a search string, and defined a database and search parameters to get the relevant studies. The list of keywords was chosen in accordance with the goals and inquiries of the research, how AI is implemented in IT Governance. Based on our objectives and study questions, we chose two major categories to determine keywords: *"Artificial Intelligence"* and *"IT Governance."* We focused on alternate spellings and synonyms to get complete findings. The final set of keywords is listed in Table 2.

The keywords were connected with Boolean operators and formulated our search string: ("artificial intelligence" OR "machine learning" OR "deep learning" OR "expert system") AND ("IT governance" OR "risk management" OR "strategy alignment" OR "value delivery" OR "performance measurement" OR "resource management")

TABLE 2
IDENTIFIED KEYWORDS

Category	Keywords
Artificial Intelligence	artificial intelligence, machine learning, deep learning, expert system
IT Governance	it governance, risk management, strategic alignment, value delivery, performance measurement, resource management

3) Inclusion and Exclusion Criteria

After obtaining the search query, we established the criteria for inclusion and exclusion.

Inclusion criteria: (I1) must be a peer-reviewed article, (I2) must be relevant to the specified search terms, and (I3) should fall within the publication date range of 2013 to 2023 to satisfy the inclusion criteria.

Exclusion criteria: (E1) Not written in English, (E2) same paper from a different database, (E3) short papers, doctoral symposium papers, conference keynote summaries, proposals, lecture notes, editorials, comments, tutorials, and review articles, (E4) papers published in predatory journals.

4) Conducting the Review

Once we established the goal, research question, search keywords, and inclusion/exclusion criteria, we moved on to this section, where we presented the results of the study search and selection process, as well as the quality assessment outcome. We present results from this stage in the "Results" section.

5) Research Search and Selection

We searched using the predefined string in the following libraries: Elsevier, Emerald, Google Scholar, Springer, and IEEE Xplore. We reviewed the titles and abstracts of each paper that appeared in the search results and determined if they met our criteria. Those that matched our criteria were added to our library for further filtering. The details of the study search process are shown in Fig. 1

A total of 359 papers were collected from multiple databases. Subsequently, a filtering process was conducted, resulting in only 40 relevant papers that met our inclusion and exclusion criteria. These selected papers were then carefully reviewed to gather more information about their content. Finally, they were matched against our assessment criteria.

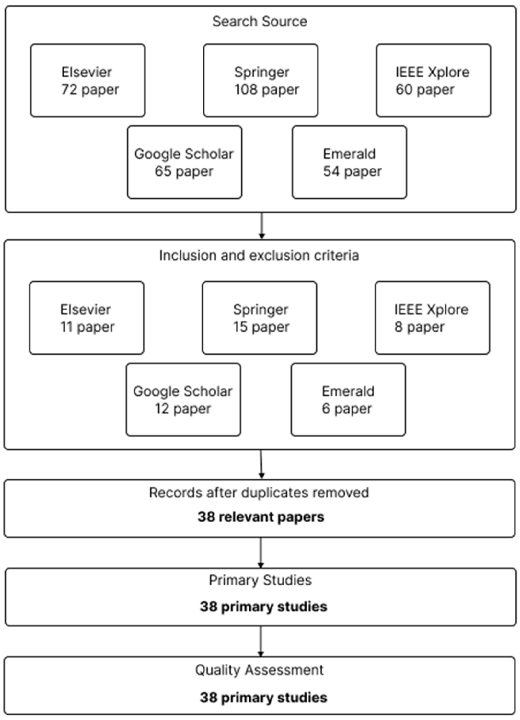

Fig. 1 Search procedure

6) Quality Assessment

We conducted a quality evaluation to analyze the methodology employed in the original research papers. We adopted the quality assessment method in references [20], [22]. Table 3 outlines the criteria employed to assess the quality of the relevant papers. All 38 primary studies underwent quality assessments. The first criterion (QA1) evaluates the objectives of each study, and all studies met this criterion positively. The second criterion (QA2) examines the level of detail provided in each study, with 92% of studies meeting this criterion. The third criterion (QA3) assesses the findings of each study, and all studies met this criterion positively. The fourth criterion (QA4) evaluates the potential for future research outlined in each study, with 63% of studies meeting this criterion. The final criterion (QA5) investigates the number of citations received by the studies, and more than five other studies cited 66% of the studies. Fig. 2 illustrates the quality assessment scores for the primary studies.

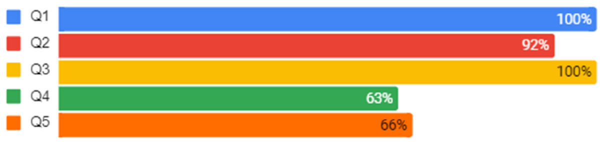

Fig. 2 Quality assessment result

IV. RESULTS

A. Summary of Studies

Our review approach led to the identification of a collective sum of 38 primary studies. The earliest study, published in 2013, accounted for one publication, while the most recent study, published in 2023, contributed two publications to the research on the use of AI in the IT governance domain. Notably, the year 2020 had the highest number of studies, with a total of eight publications. These findings are visually presented in Fig. 3, illustrating the distribution of publications over the years.

TABLE 3
QUALITY ASSESSMENT QUESTION

ID	Assessment criteria	Score	Description
QA1	Does the paper describe the goals clearly?	-1	No, goals were not described
		0	Goals were partially described.
		1	Yes, goals were clearly described.
QA2	Does the paper provide a literature review, background, and research setting?	-1	No, details are not provided
		0	Details are partially provided
		1	Yes, details are provided
QA3	Does the paper contain research results?	-1	No, future research is not provided
		0	Research results are partially contained.
		1	Yes, research results are contained.
QA4	Does the paper provide any suggestions for upcoming research?	-1	No, future research is not provided
		0	Future research is partially provided
		1	Yes, future research is provided
QA5	Do other scholarly publications reference the study?	-1	No, other publications never cited the study
		0	Other publications only cited the study 1-5 times.
		1	Yes, other publications cited the study more than five times.

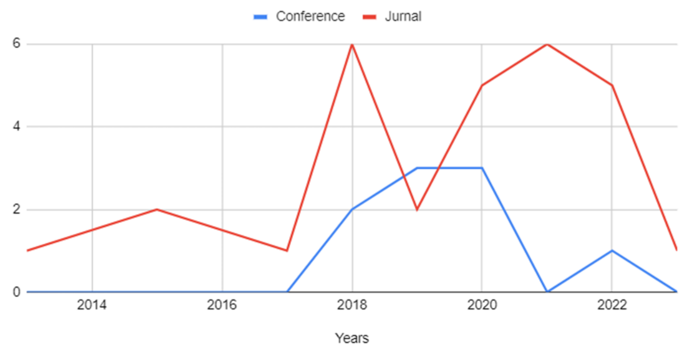

Fig. 3 Comparison of years and type of publications

B. *AI on Each Domain*

In our study, we collected and analyzed 12 papers on risk management, ten on strategy alignment, nine on performance measurements, seven on resource management, and three on value delivery in IT governance. These papers cover various aspects of managing risks, aligning IT with organizational goals, measuring performance, managing resources, and delivering value through IT initiatives. For each domain, we mapped the papers to the IT governance process based on the four stages of the Deming Cycle: Plan, Do, Check, and Act, as shown in Table 4. In Table 4, we mapped each paper based on the IT governance domain, the relevant Deming cycle stage, and the AI implementation goal.

1) *Risk Management*

Risk management is how a company becomes aware of and manages risks. Effective risk management necessitates senior corporate officers to be conscious of potential risks, have a thorough comprehension of the enterprise's willingness to take risks, be knowledgeable about compliance obligations, be transparent about the significant risks that could impact the enterprise, and integrate risk management responsibilities throughout the organization [22].

TABLE 4
STUDIES OF DOMAIN BREAKDOWN

Domain	Reference	Deming Cycle	AI Implementation
Risk Management	[23]–[26]	Plan	Comparing the method for each study case
	[27], [28]	Plan	Optimizing the model as a new method
	[27], [29]–[32]	Do	Analyzing data
	[33], [34]	Do	Validity method
	[25], [27], [28]	Check	Evaluating model
Strategy Alignment	[35]–[39]	Plan	Help construct an organizational strategy
	[40]	Do	Recommend product suggestions to the customer
	[41]	Do	Determine project priority that aligns with organizational strategies from project portfolios
	[42]	Do	Align business pattern
	[37], [40], [43]	Check	Evaluating strategies
	[44]	Check	Evaluating business processes
	[36]	Check	Measuring strategic alignment maturity level
Value Delivery	[41]	Plan	Optimization model for speeding up decision-making processes.
	[45]	Do	AI entails a certain amount of human control and decision-making
	[44]	Do	Evaluate two artificial models and calculators
Performance Measurement	[46]	Plan	Validity test confirmatory factor analysis (CFR)
	[46]	Do	Assessing moderating effects of change leadership
	[47]	Do	Identifying new employees' position
	[47], [48]	Do	Increasing business performance
	[28]	Do	Assessing risk in software projects
	[49]	Do	Predicting defects in the system
	[49]	Check	Performance analysis of the defect model
	[50]–[53]	Check	Predicting and Measuring business performance
Resource Management	[54]–[58]	Plan	Estimating the cost and effort of Software Development
	[59]	Plan	Predicting the cost of repairing fiber optic
	[60]	Plan	Determination for Choosing IT Vendor or IT Outsourcing

In the risk management domain, the implementation of AI is predominantly focused on the Plan and Do steps, with a few instances in the Check steps but none in the Act steps. AI is primarily utilized for comparing machine learning and deep learning methods to determine the optimal approach for specific study cases. A study in [23] identified the optimal method for measuring credit risk using a classification approach. The study in [24] measures potential security attacks using semantic analysis. In [25], several supervised algorithms for prediction were compared to determine the best security control for each study case. A study [26] identified the most effective classification method for measuring regulatory violations. Additionally, AI is also incorporated into new methods. The study in [27] introduced a novel approach to software defect prediction. The study in [28] developed a new hybrid machine-learning mechanism for risk assessment in software projects.

In the Do steps, AI is predominantly used for data analysis. The study in [27] analyzed the results of each method and compared them with a new method. A study [29] analyzed customer default data in e-commerce using classification methods. Reference [30] analyzed data to measure the level of trust in service and reduce the risk of making wrong choices. Reference [31] analyzed data to predict Common Weakness Enumeration (CWE). Reference [32] created layered analysis with a Deep Neural Network. In the Do stage, AI is also used to validate a method. A study in [33] tests the accuracy of vulnerability automation, while reference [34] measures critical project success based on experience.

In the Check steps, only a few papers have mentioned how AI is implemented in their study cases. Reference [25] evaluates data models to choose the best security approach, while studies in [27] and [28] evaluate data results to compare their new methods with other existing methods. However, papers have yet to be found that implement AI in the Act steps.

2) Strategy Alignment

According to a study in [35], aligning business requirements with IT resources continues to be a significant and concerning area of focus. Reference [35] explains how a model such as the Strategic Alignment Model (SAM) can help with the alignment between business and IT needs, where the cross-domain alignment is depicted in two aspects: strategic adjustment (connecting the external and internal domains) and functional integration (bridging the business domain and the IT domain). And as [61] advocates, the SAM was designed for high-level managers. That is why Artificial Intelligence can offer high assistance for the strategic alignment field of an organization. Just as [36] stated, by integrating AI in Strategic Alignment, the decision makers or high-level managers can be provided top-tier information that was attainable solely through the adoption of technology and business intelligence.

This justified the idea that Artificial Intelligence can positively impact the strategic alignment field within an organization, mainly in the Plan stage of strategic alignment, with some instances in the Do and Check stage. AI is utilized the most in the planning stage, as it helps with decision-making and strategic planning for business. Reference [36] shows that AI can help to construct a good marketing strategy by giving information to the decision-maker. The study in [37] also confirms this, showing that AI can construct a strategy to retain customers by analyzing past data. The study in [38] justified it by showing how AI is utilized to analyze data to help construct and align IT-Business strategy. Reference [39] concludes that AI has the capability to handle various complex problems, such as traffic management in the transportation sector or distributed energy systems in the energy sector. While the others show how to utilize AI for analyzing data, [35] shows how it can also be used to help the data circulation within the organization so the data flows better and each part of the organization can access the same and best information.

Even though it feels like AI is used most in the Plan stage by analyzing data, [40] shows that analyzing data can also be used in the Do stage, as it can be used to analyze customer behavior and recommend products to customers based on customer expenses. The study in [41] also shows other uses of AI, as it can also be used to pick and choose projects from an organization’s project portfolios that are most similar to the current projects or strategies the organization is executing. The study in [42] even shows that AI can identify and align the organizational pattern in business processes, etc.

Finally, AI can also be utilized in the Check stage of IT Governance [40], which shows that after it gives product recommendations to the customer, it can also evaluate the effectiveness of those recommendations to find ways to improve. Reference [37] also shows the same thing with customer retention strategy: how AI is used to help analyze data to help strategy construction and can also be used to evaluate the strategy. The study in [43] shows AI being used to analyze and evaluate the organizational business model and business process to see if there is a problem with the process and/or model. The study in [44] even concluded that AI integration in the strategic alignment could also positively impact the evaluation of the maturity of implementation of strategic alignment within the organization. The study in [36] investigates the strategic alignment between IT strategies and offers a model for decision-makers in production to enhance operational performance. In this case, AI is used in the planning phase to assist operations executives in making effective decisions. This concludes that within the Deming Cycle, the benefit of AI can be felt the most in the Plan stage, with some instances in the Do and Check stages of an organization’s strategic alignment.

3) Value Delivery

Ensuring that IT investments align with an organization's strategic business objectives and provide value to the company is referred to as the IT value delivery domain in IT governance. This area ensures that IT services meet the organization's aims and objectives and that IT investments align with strategic goals [62].

References [41] propose an optimization model to speed up the IT program and portfolio decision-making processes. The multi-objective model determines the best combination of project types, and the solution approach effectively generates more effective suggestions than those discovered using the most recent empirical techniques.

AI implementation [45] emphasizes that using AI entails a certain amount of human control and decision-making. What has evolved is how the end objective is accomplished and how AI could help accomplish this objective. The study in [44] used AI to evaluate the "Diab BITA Model" and the "Diab Calculator," two artificial models and calculators the author created.

4) Performance measurement

Performance measurement is monitoring, tracking, analyzing, and improving IT performance. One of its main focuses is to measure the performance of companies using the balanced scorecard [63]. Managing the performance of governance, using AI or other AI-related methods as its core process, is likely to reduce cost, time, and give the means to help manage a company's performance automatically.

Reference [46] explained the use of AI to support data analysis for conducting validity test confirmatory factor analysis (CFR) to assess its loading factor, reliability, robustness, and suitability of the data on employee performance and work engagement. Apart from the validity test, common method bias and goodness-of-fit model were implemented to examine the fit of the four-factor model by utilizing AI as its practice. From this finding, AI benefits in the Plan steps of the Deming Cycle in pursuit of performance.

Many business practitioners apply AI to help with decision-making. One of its applications is mentioned in [47], where a model of machine learning method was implemented to assist the human resource management process. The combination of text mining and machine learning will help comprehend a much larger pool of candidates to identify the best candidates for the correct position. Another practice of AI is also stated in [46], suggesting a model of SEM, according to its theoretical hypotheses, to adopt and assess the direct and moderating effects of change leadership. As asserted in [48], the use of AI in the hotel industry is not limited to enhancing hotel services but also to adapting to other AI models, facilitating communication for both internal and external components, managing information, and handling multiple tasks to increase hotel performance. Assessment is commonly associated with the work of AI, affirmed in [28], by using the adaptive neuro-fuzzy inference system-based multi-criteria decision-making (ANFIS MCDM) and intuitionistic fuzzy-based TODIM (IF-TODIM) approach to assess risk in software projects. The [49] expressed that it is possible to detect a fault in the system using the deep neural network and genetic algorithm method and, as it will enhance its efficiency of defect prediction. Combining the use of AI and convolutional neural networks (CNN), [47] built a model of performance research in hopes of improving business management performance. Using real-time data as the input, the system creates a complete analysis of the performance test using the dimensional weight. Apart from business sectors, AI has made its presence known in the medical industry, implicated in [50], as the tool to diagnose diseases and help with other medical services in hospitals by integrating AI and increasing performance. From this overview, AI also benefits in the Do steps of the Deming Cycle.

The findings of AI activities in [51] helped weighted the country ranks by implementing the fuzzy method to measure the performance of the firms. Since the international activities of said firms contribute to the environment, it is essential to positively influence the prosperity of countries. The mobile cellular network problem [52] is another example of AI implementation using machine learning. Gaussian process regression, exponential smoothing of time series, and random forests assisted in performance prediction as they significantly reduced cost and improved user experience. Critical factors of enterprise resource planning (ERP) can be measured through AI, as claimed in [53], to find its cause to further broaden the benefits of ERP. A balanced scorecard is a familiar approach to achieving measurement in performance as it can be expanded with other machine learning methods to aid its decision-making model further. Similarly, [49] mentioned how AI can perform analysis using machine learning for defect prediction models. Medical evaluation is another approach of AI [50] that can give medical reports and risk management. From this discovery, AI benefits in the Check steps of the Deming Cycle to assist in performance measurement.

5) Resource Management

Resource management is the optimal investment, optimization of knowledge and infrastructure as key issues, and proper of critical IT resources, such as applications, information, infrastructure, and people [64]. Resource Management focuses on managing existing resources within the scope of the company's IT needs effectively and efficiently, starting from identifying resource requirements, determining the required resource budget, usage management, and maintenance. This domain also includes managing resources to become optimal company investments that earn more profits.

The study in [54] aimed to create a machine learning model for predicting software development effort estimation by comparing several algorithms and finding the algorithm that has the best accuracy. This research results show that the decision tree algorithm has the best accuracy compared to other algorithms with three measurement metrics: MMRE, PRED, and R2-Score. Reference [55] created a comparison of several machine learning algorithms to determine software cost estimates. The results showed that the Random Forest algorithm machine learning method has the highest accuracy compared to other algorithms and can be used to predict software costs with a high accuracy rate using five evaluation measurement metrics, namely R^2, MAE, RMSE, RAE, and RRSE. Reference [56] determined the cost and effort required and consequently affect the overall success of software development using machine learning methods. Naïve Bayes and Random Forests compared these machine learning models using the ROC curve and Confusion Matrix best. This research shows that the Naïve Bayes algorithm outperformed the other two techniques in the ROC curve and Recall score. However, the Random Forests algorithm had a better Confusion Matrix and scored better on the classification accuracy, and precision measurements. Reference [57] created a machine learning model using an ensemble method of three machine learning algorithms (Support Vector Machines, Neural Networks and Generalized Linear Models) to estimate effort and duration intended to provide a decision support tool for organizations that develop or implement software systems. The average of the three methods obtains the final result. The study in [58] proposed that the Spiking Neural Networks improve the accuracy of process cost estimation, improving software quality with two measurement metrics, namely RMSE and MMRE. In the Deming cycle, the machine learning model can be implemented in the Plan phase as it can support software project managers in determining and minimizing effort and cost for each software project while leading to timely completion and proper management of project resources.

Reference [59] aimed to investigate the cost of repairing underground fiber cable failures, classify the causes of faults and predict the cost of repairing faults in the future. K-means clustering can provide balanced grouping with accurate centroid computation in classifying fiber cables based on the causes of failure, repair costs, and geographic areas of fault occurrence. The multilayer perceptron FFNN or the predictive model has been able to accurately predict the cost of repairing pieces of underground fiber cable using three measurement metrics, such as CC, MAE, and RMSE. In the Deming cycle, the predictive model is included in the Plan phase because it can support the telecommunication industry in knowing the cost of repairing underground optical networks before disturbances occur, depending on which area, causes of failure and mean time to repair (MTTR) and inform cellular network operators of the costs required to repair damaged cables.

The study in [60] proposed helping companies or organizations outsource IT or choose the right IT vendor using Natural Language Processing and Machine Learning methods. Multinomial logistic regression performs better than the other three methods (Random Forest, XGBoost, and Neural Network). In the Deming cycle, the model is included in the plan because it can help companies find the right IT vendor to meet the appropriate IT resources.

V. DISCUSSION

Our research and analyses show that AI has emerged as a powerful tool with the potential to enhance decision-making and optimize organizational processes. However, its application in different stages of the governance process is unevenly distributed. During the initial Plan stage of IT governance, we discovered that each domain has at least one research paper dedicated to AI implementation. We found a total of 20 papers in this stage, with a particular focus on integrating AI in the risk management and resource management domains. Moving on to the Do stage, only the resource management domain had no identified cases of AI implementation. However, we still came across 19 papers highlighting the use of AI, with a strong emphasis on its application in performance management. In the Check stage, we observed a clear trend where AI implementation was most prominent in the performance management domain. On the other hand, the value delivery and resource management domains showed a lack of AI integration. 13 papers shed light on successfully incorporating AI in the performance management domain. Lastly, in the Act stage, it was interesting to note that we did not find any papers that explored AI implementation, indicating a unique characteristic of this stage in organizational decision-making.

In the Risk Management domain, AI is employed through comparative methods to select the most accurate options or analyze security measures to mitigate vulnerabilities. Risk Management involves the identification of both tangible and intangible assets that require protection, assessing potential threats that these assets may face, and determining the level of vulnerability each asset has in relation to a specific threat [15]. Similarly, Strategy Alignment encompasses aligning the perspectives, positions, plans, and patterns of both the enterprise and IT [15]. AI implementation also takes precedence in the Plan, Do, Check steps. In this domain, AI is used in many ways, such as analyzing to help decision-makers, identifying data patterns, and evaluating the effectiveness of strategies. Otherwise, in Performance Measurements, AI is also used in Plan, Do, and Check steps. However, it is dominantly used in check steps, unlike the two domains that have been mentioned before. Performance measurement is defined as monitoring, tracking, analyzing, and improving IT performance. One of its main focuses is to measure the performance of companies using the balanced scorecard [63]. AI in performance measurement mainly focuses on optimizing, predicting, and measuring the implemented system to enhance organizational activity. AI was able to carry out its purpose with the help of real-time data, and it is mostly used to measure performance in business.

In contrast, in the Value Delivery and Resource Management domains, the use of AI could be more extensive. Only three papers discussed AI implementation in the Value Delivery domain. Value Delivery focuses on meeting customer expectations and achieving business outcomes based on customer preferences and perceptions. [15]. The identified papers showcased AI implementation in the planning and execution stages. Specifically, AI-enhanced portfolio decision-making processes and evaluated artificial models and calculators. AI implementation in value delivery aims to improve the effectiveness and efficiency of achieving end objectives while retaining human control and decision-making. In the resource management domain, we found a more significant number of papers; however, their implementation of AI was confined to the planning stage. Resource management primarily involves managing various resources such as finances, software and applications, hardware and infrastructure, information and data, and people[15]. AI implementation in this domain focused on software development effort estimation, software cost estimation, cost and effort determination in software development, project resource management, and fault classification and prediction in the telecommunication industry. We can't find how AI is implemented in every domain's act phase of the Deming cycle. In this case, the Act stage is where AI is used to implement the improved solution [65].

The differing use of AI across the stages of IT governance is driven by its unique capabilities and the specific focus of each domain. AI technologies can streamline organizational governance by reducing costs associated with regulatory integration, control management, compliance data processing, knowledge discovery from databases, and information retrieval from vast amounts of data [4]. Understandably, AI implementation varies across domains and within each step of the Deming cycle. Reference [66] stated that most AI applications cannot perform well in different contexts. This is because they are often trained on data specific to a particular context and may need help to generalize to new contexts. This can be a significant challenge for AI applications, as it limits their potential to be used in a wide range of settings, and this can answer the question to why AI is more capable of being used in the Plan, Do, and/or Check stages of the Deming Cycle as it is still limited to the contexts of all the other things that are not presented as raw data, and so limiting its use in the Act stage of AI implementation.

Despite the first reason, some other challenges and limitations hinder the widespread implementation of AI. One significant challenge is the need for clear guidelines and frameworks for integrating AI into existing governance processes. The absence of standardized practices makes it difficult for organizations to navigate ethical considerations, address data privacy concerns, and ensure fairness and transparency in AI-driven decision-making. This is where AI governance plays a crucial role. The institutions and environments in which AI is created and used are the focus of AI governance. In particular, AI governance aims to increase the possibility that those who develop and use advanced AI have the objectives, motivations, worldview, time, training, resources, support, and organizational framework required to advance humanity [19]. It is designed to address AI's ethical, legal, and social implications. However, evaluating the status and maturity of these initiatives is difficult because AI governance is generally in its early stages. It needs to have a sufficient duration to assess the outcomes of specific actions, and there's still a need for more standardization within individual organizations. As technology and governance initiatives progress and develop, their effects will become increasingly apparent [67]. Understanding the strengths and limitations of AI helps organizations make informed decisions about its implementation and maximize its potential in improving IT governance processes.

In the future, AI holds vast potential within the realm of IT governance. As AI technologies advance, organizations can enhance their decision-making procedures, boost operational efficiency, and refine risk management practices. AI can process extensive data, recognize patterns and trends, and deliver valuable insights to inform decision-making. It can automate repetitive tasks, reduce human errors, and optimize resource allocation. Additionally, AI-powered predictive analytics can enable organizations to anticipate and mitigate potential risks effectively. The study in [18] explained key axes to implement AI in business strategy, while a study in [3] explained how AI could be used in the digital era. By harnessing the potential of AI and ensuring responsible implementation, organizations can unlock new opportunities and drive innovation in their IT governance practices.

Some limitations in our study can be addressed in future work. Our study did not review the specific AI methods used at each stage of the Deming cycle. There are several exciting research opportunities to explore in AI and IT governance. Firstly, further investigation into the ethical considerations and implications of AI implementation in IT governance is crucial. Understanding the potential biases, transparency challenges, and accountability frameworks associated with AI systems will help develop guidelines and best practices for responsible AI governance. Integrating emerging technologies like blockchain, the Internet of Things (IoT), and cloud computing with AI in IT governance can uncover novel approaches to data management, security, and decision-making processes. Furthermore, conducting comparative studies across different industries and organizations to evaluate the impact and effectiveness of AI in IT governance will provide valuable insights for future implementation strategies. Finally, developing robust AI governance frameworks, regulations, and standards will be instrumental in ensuring AI's ethical and responsible use in IT governance. By addressing these research areas, we can unlock the full potential of AI in shaping the future of IT governance practices.

VI. CONCLUSIONS

This study has a valuable contribution by exploring the applications of AI in each domain of IT Governance, especially with regard to the Deming cycle. Through an analysis of existing literature, we observed that AI has emerged as a powerful tool with the potential to enhance decision-making and optimize organizational processes. However, its application across different stages of the governance process is not uniformly distributed. AI implementation is more prevalent in the Plan, Do, and Check stages, emphasizing risk management, strategy alignment, and performance measurement. On the other hand, AI integration in the Value Delivery and Resource Management domains is relatively limited. The varying use of AI in IT governance is influenced by the unique capabilities of AI technologies and the specific focus of each domain. Additionally, challenges and limitations exist, including the need for clear guidelines for integrating AI into existing governance processes and the immaturity of AI governance as a field. Despite these challenges, the potential of AI in IT governance is immense, with expectations of enhancing decision-making, optimizing operational efficiency, and fortifying risk management. Future research should explore the ethical implications of AI implementation, integrate emerging technologies with AI in IT governance, conduct comparative studies across industries, and develop robust AI governance frameworks. By addressing these areas, organizations can fully leverage the benefits of AI in shaping the future of IT governance practices.

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