An Evaluation of The Current State of Risk Management Practices and The Level of Awareness on Machine Learning Among Information Technology (IT) Project Managers

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Abstract

This study aims to leverage machine learning (ML) for adaptive risk management in Nigerian information technology (IT) projects. The study's specific goal was to assess the present state of risk management procedures and ML awareness among IT project managers in Nigeria's Abuja, Lagos, and Rivers states. The study used snowballing and purposive selection strategies to pick 900 respondents from a finite population of 1000 practitioners, utilising the Cochran's method for sample size determination. The data collection and survey instrument included a well-structured questionnaire, performance statistics, and IT project site visits. The acquired data was presented in the form of frequency distribution tables, charts, and figures using descriptive statistical methods, specifically IBM SPSS Statistics version 26.0. Mean score ranking and the relative importance index (RII) were employed to evaluate the study's primary objectives. The study's findings indicate that risk management is still mainly immature and informal in Nigerian IT projects. The utilisation of quantitative risk analysis techniques (MIS=2.45) and specialised software tools (MIS=2.35) was extremely low, indicating that qualitative methods, manual procedures, and no analytical approaches are being used. Moderate scores for risk identification (MIS=3.15) and response planning (MIS=3.05) indicate a basic understanding of risk management concepts, whereas low scores for formal processes (MIS=2.85) and learning from previous projects (MIS=2.75) indicate a systematic lack of institutionalising risk management practices. The study also found that the majority of IT project managers are at the "Aware" or "Knowledgeable" level of ML, but only 14.7% have advanced to the "Applied" level, demonstrating a significant gap between knowledge and actual application. This report suggests that IT organisations use complete risk management frameworks, such as explicit policies, risk registers, and regular evaluations. Government and professional bodies should encourage ML adoption and training programs, which will lead to better risk management in IT projects.

Keywords: *Machine learning, Information technology, Relative importance index, Projects.*

Introduction

Artificial intelligence (AI) was first established in the 1950s with the intention of using computers to replicate human intelligence (Nnadozie, Amade, & Enyinna, 2026). Although the field of artificial intelligence has seen significant fluctuations over the years, owing primarily to a mismatch between expectations and available applications, it appears that current AI technologies are mature enough to provide significant improvements in various aspects of the workplace, including project operational and managerial processes.

Artificial intelligence (AI) is gradually becoming a strategic asset in a variety of businesses, allowing for automated decision-support, enhanced analytics, and real-time insights. AI use in project management (PM) has expanded dramatically in recent years, with global market predictions predicting a growth from USD 2.5 billion in 2023 to USD 5.7 billion by 2028. The global economy is becoming increasingly reliant on the effective completion of information technology (IT) projects, which promote digital transformation, operational efficiency, and competitive advantage across all industries (Standish Group, 2020). However, information technology projects are inherently complex and risky, with a high failure rate. The Standish Group's CHAOS Report repeatedly shows that a significant proportion of IT projects fail to reach their objectives, with common difficulties such as cost overruns, timetable delays, and unmet stakeholder expectations.

Machine learning (ML), a subset of artificial intelligence (AI), represents a paradigm shift in risk management. ML algorithms can use historical and real-time project data to discover complicated, non-linear trends and anticipate potential risks before they occur (Bishop, 2006). This capability offers a proactive and adaptable approach to risk management, with risk response tactics that can be dynamically altered to reflect changing project conditions. While the use of machine learning in project risk management is gaining popularity around the world, its use in Nigeria's IT sector is still in its early stages and mostly unexplored in academic literature. As a result, the purpose of this research is to look into the feasibility of using machine learning to develop an adaptive risk management framework adapted to the Nigerian IT project environment. Machine Learning (ML), a subset of artificial intelligence, provides new prospects for improving risk management in IT projects (Nwankwo, 2026). In near-real time, ML systems can analyse past project data, identify patterns, forecast possible dangers, and provide mitigation solutions. ML's learning capabilities lay the groundwork for adaptive risk management, a dynamic strategy that reacts to emerging hazards and changing project contexts.

Despite the growing relevance of using ML to enhance adaptive risk management in information technology projects in Nigeria, there is still a scarcity of evidence on IT projects, particularly in Nigeria. Unfortunately, relatively few studies have used ML to enhance adaptive risk management in fields other than Information Technology projects in Nigeria. Furthermore, there are limited research on applying machine learning for risk management in Nigeria. Examples include (Pam, 2026) risk management in the banking sector; a strategy for utilising AI and big data in Africa's financial risk; and predictive modelling and risk mitigation in education and finance. According to the Central Bank of Nigeria (Pam, 2026), risk management is still in its early stages and faces numerous problems. These difficulties include low risk management understanding among many bank board members and a shortage of professionals. Others include a lack of risk training and education, as well as a framework that promotes the growth of qualified and capable industry professionals.

Despite machine learning's global success in industries such as finance, healthcare, and software development, its application in project risk management in Nigeria—particularly in the IT sector—is mostly unexplored. As a result, the purpose of this study is to look into how machine learning may be used to improve adaptive risk management in Nigerian IT projects by defining major risk variables, reviewing current practices, and suggesting a feasible implementation approach.

Historically, many IT projects have failed, the CHAOS Report produced in 2004 by the Standish Group revealed that an eye-brow raising 53% of software projects were neither delivered on schedule, within budget nor with the required functions (Samadi et al., 2014). Meanwhile a further 18% of these projects were cancelled. Numerous surveys routinely report the high-risk nature of

IT introduction and usage and reflect the hidden-cost process of such projects. For example, a survey that reviewed 200 IT project organizations over the past decade, found that 90% of projects costing over $660,000 were over budget, 98% had specification alterations, 60% had overrun their schedules and 20% were deemed to be unsuitable. These failures could be due to high risks involved in all IT projects (Nwankwo, 2026).

The Nigerian information technology sector is an important engine for national development, but it is hampered by a high rate of project failure. These failures result in substantial financial losses, squandered resources, and lost possibilities for socioeconomic growth. The root of the problem is the inability of traditional, static risk management approaches to adequately negotiate the volatile, unpredictable, complex, and ambiguous (VUCA) environment in which Nigerian IT projects operate.

Literature Review

Tüysüz and Kahraman (2006) contended that there is a substantial association between the quantity of risk management carried out in a project and its level of success; more successful projects use more risk management techniques. They also discovered that project risk management strategies are associated with success in meeting schedule and budget objectives, which is one of the most prevalent risks encountered in most projects.

Because unforeseen or uncontrolled risks are two of the leading reasons of project failure, organisations or project teams must be prepared to handle project risks in order to achieve the required level of project success. This entails being aware of and managing project risks. Risk management in projects has been practiced since the mid-1980s, and it is one of the Project Management Institute's nine major knowledge areas. Effective risk management will boost the success rate of an IT project in terms of cost savings, product or service quality improvement, and project completion expectations (Baharuddin & Yusof, 2018). However, risk management is frequently viewed as an alternative to project management, resulting in inconsistent risk management techniques. In certain circumstances, project managers only focus on some of the risk management processes, resulting in the project's risk not being handled consistently and comprehensively.

The Project Management Institute (PMI, 2021) defines project risk as an unpredictable event or condition that, if it occurs, has a positive or negative impact on one or more project objectives such as scope, time, cost, and quality. While Kutsch and Hall (2005) described risk management in a project setting as the systematic process of detecting, evaluating, and responding to uncertainty as project-related occurrences or conditions that are unknown but have the potential to have a negative impact on a project's purpose.

Projects, according to Ajibola, Omiyale, and Ogunwolu (2018), can encounter unanticipated challenges because no project is riskless. Risk can be defined as the probability that an action or activity will result in an undesirable consequence or, in extreme cases, a loss of any kind. It refers to any unforeseen incident or condition that may affect the success of a project. It is the exposure to the possibility of events occurring that will have a detrimental or positive impact on project objectives due to uncertainty. A risk in an IT project is the probability of experiencing loss, which can take the form of low-quality software solutions, increased expenses, failure, or delayed completion (Baharuddin & Yusof, 2018). Risk management is a process, strategy, instrument, or approach that helps project managers identify, control, prevent, and solve risks so that the project's objectives, requirements, and goals are satisfied.

Traditional risk management frameworks

All initiatives include inherent risks due to their unique nature, varying complexity, restrictions, and stakeholder expectations. Successful project risk management aims to identify and manage risks that may jeopardise project objectives (Geamanu et al., 2026). Individual risks might affect specific project objectives, whereas overall project risk represents the combined effect of all uncertainties. Project risk management techniques seek to reduce negative risks (threats) while maximising positive risks (opportunities). Managing total project risk entails minimising unfavourable variances, maximising good outcomes, and maintaining a high probability of meeting project objectives.

Risk Identification

Castillo-Ñopo et al. (2024) suggest that identifying risks involves more than just listing probable setbacks. Rather, it requires a thorough examination of all aspects of the project and its interactions. Technical, operational, financial, and human resource issues are thoroughly investigated, revealing links that potentially cause problems. Similarly, opportunities are identified that could be used to increase the project's efficiency or value. Meanwhile, Baharuddin and Yusof (2018) describe a management strategy that collects and interprets data to support project decisions. During the risk identification phase, a checklist is created using brainstorming to identify any risks that the project may face. This technique is closely related to the project's success.

Risk evaluation

Is the process of determining the significance and probability of recognised risks. The goal of risk evaluation is to determine the significance of risks and prioritise them based on their impact on project objectives for future attention and action (Tüysüz & Kahraman, 2006). Evaluation techniques can be divided into two categories: qualitative approaches and quantitative methods. Qualitative techniques highlight the features of each danger in enough depth to make them understandable. Quantitative techniques use mathematical models to simulate the impact of risks on project results. Quantitative analysis, such as Monte Carlo simulation and decision trees. Is the numerical analysis of the aggregate impact of recognised individual project risks and other sources of uncertainty on overall project objectives (PMI, 2017).

Risk Response Planning

Developing methods such as avoidance, transfer, mitigation, and acceptance. Planning risk responses entails taking efforts to improve opportunities and mitigate threats to project success (Schwalbe, 2019). Using the results of the preceding risk management processes, project teams can create risk response plans, which frequently result in change requests, modifications to the project management plan, and project documents.

Risk Monitoring and Control

Tracking identified hazards, monitoring residual risks, and detecting new ones. It entails monitoring identified and residual risks, detecting new risks, implementing risk response plans, and assessing the success of risk measures during the course of the project (Schwalbe, 2019). Risk control is where strategy meets execution, bringing risk management from theory to practice. It is not just about minimising dangers, but also about developing proactive strategies to build resilience and prevent detected risks from escalating into operational crises. Risk control serves as

a safeguard by incorporating preventative measures, contingency plans, and adaptive strategies into an organization's framework to mitigate uncertainties before they occur (Afolabi et al., 2025).

The AI, IT Risk and machine learning paradigm

The Fourth Industrial Revolution has improved risk management through the use of digital technologies. Mutanda, Mtombeni, Tapera, and Mashapure (2025) argue that dangers in today's business environment are frequently too complex and unexpected for traditional risk management procedures to properly address. Using digital technologies in risk management can automate risk assessment processes, which is a significant advantage. Digital technology has transformed the discipline of risk management by enabling firms to improve cooperation and communication, automate and streamline procedures, and improve the accuracy and efficacy of risk assessments. AI, according to Ajibade et al. (2025), adds adaptive and predictive capabilities that outperform traditional risk solutions. AI tools such as machine learning algorithms, neural networks, and natural language processing allow businesses to spot trends, abnormalities, and early warning signals that would otherwise go undetected using traditional risk assessment methods (Ajibade et al., 2025).

AI is defined as "the science and engineering of creating intelligent devices, particularly intelligent computer programs" (Forster & Strauss, 2025). While it is impossible to provide a precise description of AI, we make a rudimentary attempt to segment it. In terms of machine learning, this study distinguishes between weak and strong AI. The former just simulates the decision-making process, whereas the latter learns from past experiences and makes its own decisions. Cloud-based collaboration platforms, AI chatbots, and virtual reality platforms facilitate open communication and information sharing among stakeholders, leading to greater risk assessment and decision-making (Mutanda et al., 2025). Leveraging digital technology creates opportunities for businesses to increase resilience and risk management by addressing complex challenges. Machine Learning (ML) has altered project risk prediction by introducing adaptive, data-driven algorithms that have been found to beat older non-adaptive models (Abaneme et al., 2025). Machine learning (ML), natural language processing (NLP), and neural networks have the ability to increase forecasting accuracy, uncover early warning indications, and facilitate decision-making in high-risk infrastructure scenarios (Odekunle et al., 2025). When utilised to model complex infrastructure networks, such technologies can generate predictive analyses for cost and schedule overruns, manpower shortages, equipment failures, and environmental disruptions, allowing the project manager to respond proactively rather than reactively.

Despite the obvious benefits of AI technology in risk management, their implementation is fraught with data privacy, security, and ethical concerns, such as potential bias and the need for openness. The "black box" aspect of some AI models, particularly in machine learning, hampers understanding of their decision-making processes, raising questions regarding responsibility (Nwankwo, 2026). GenAI can help project managers identify difficulties, seek assessments based on industry data, and acquire best practices or step-by-step advice (Geamanu et al., 2026). AI models can also mimic project outcomes under alternative assumptions, allowing teams to evaluate and refine their plans. Iterative use, along with human verification, enables AI systems to improve outputs over time and better fit with organisational needs. While GenAI improves overall project management capabilities, its potential is especially great in specialised fields like risk management, where predictive analytics and automated assessments can significantly boost project resilience.

One of the requirements for AI application in infrastructure risk management is a safe digital environment, which includes sensors, IoT, databases, and platform integrations (Odekunle et al., 2025). In most emerging nations, insufficient digital continuity, weak cloud infrastructure, and a lack of uniform data formats make it difficult to construct real-time risk prediction models. In Nigeria, weak institutional arrangements and a lack of investment in project data systems sometimes impede the execution of digital transformation strategies. According to research, building block investments in data governance, open data standards, and public-private technological collaborations are required to enable AI risk applications. AI systems assist decision-making by facilitating real-time risk alerting, maximising resource utilisation, and providing project outcomes under various scenarios. Predictive analytics is evolving into a smart, automated, and real-time risk governance facilitator.

Emerging research illustrates the potent application of machine learning in boosting project risk management, including the following:

Predicting Project Success/Failure: Supervised learning models based on past project data (e.g., beginning estimations, team size, requirement volatility) have been constructed to accurately predict the chances of project success (Cheng et al., 2020).

Cost and Schedule Overrun Prediction: Regression algorithms can use project performance measures (such as Earned Value Management data) to anticipate ultimate costs and completion dates, allowing for early corrective action (Akinsola et al. 2020).

Anomaly Detection for Proactive Risk Identification: Unsupervised learning can monitor real-time data streams from project management tools (e.g., Jira, GitHub) to detect deviations from normal patterns, such as a sudden drop in productivity or a spike in defect density, which indicate potential risks (Zhang & Wang, 2021). These applications indicate to a future of "adaptive" or "cognitive" risk management, in which systems constantly learn and deliver data-driven insights, moving away from the static character of previous techniques. For robust risk assessment, risk analysis methods include simulation (Monte Carlo) and AI, with prediction models such as decision trees and logistic regression used to discover and classify risk indicators (Adamantiadou & Tsironis, 2025). Figure 1 highlights the AI models used in project risk management and forecasting. It shows how various AI approaches are used to discover, assess, and mitigate risks. From FL systems for risk prediction to complicated neural networks for performance forecasting, the decision tree demonstrates how risk management techniques evolve as AI tools are applied.

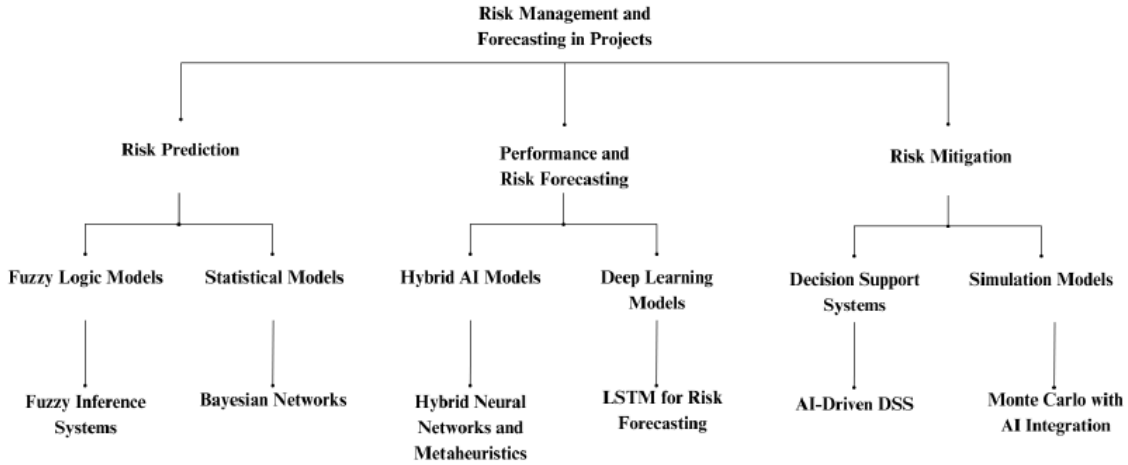


Figure 1: AI models used for risk management and forecasting within projects (Source: Adamantiadou & Tsironis, 2025).

Research Methodology

This study used a mixed-methods design, with three distinct phases. This design was optimum since it enables for in-depth investigation of the phenomenon prior to creating and testing predicting models (Creswell & Plano Clark, 2017). According to Okong'o (2022), the target population is a collection of all elements or items being studied in order to reach a conclusion in a research endeavour. This study's target population consists of professionals and organisations involved in IT projects in Nigeria, such as IT project managers, software developers and engineers, business analysts, IT consultants, and organisations undertaking IT projects across various sectors (e.g., finance, telecom, healthcare).

The study used the snowball sampling technique with a sample size of around 900 respondents (calculated using Cochran's formula with 95% confidence level and 5% margin of error). The strata were determined based on the respondents' professional roles, industrial sector, and years of experience. The purposive sampling technique (saturation sampling) was then used, with approximately 20-25 experts participating. The professionals were chosen based on their experience in IT project management in Nigeria, which required at least 5 years.
A systematic questionnaire was created, with the first section addressing demographic issues such as professional background and experience, organisational features, and project types and scales. The second section evaluates risk management strategies, including existing risk identification methods, risk analysis techniques employed, risk monitoring frequency and instruments, and the effectiveness of current practices in relation to IT projects (5-point Likert scale). While the final portion discusses machine learning preparation, awareness and comprehension of ML principles, organisational readiness for ML adoption, etc.

Following data collection, a percentile, frequency table, pie chart, and bar chart were utilised to assess the respondents' demographic characteristics on a nominal scale. The other part of the ordinal scale was evaluated using the Statistical Package for Social Sciences (SPSS 26.0). To assess the existing state of risk management procedures and awareness of Machine Learning among Nigerian IT project managers. The mean item score was utilised to assess this objective. The mean item score was used to calculate the average of the factors influencing the advantages of IT project risks. The current state of risk management techniques and IT project managers' awareness of Machine Learning were graded in order of value, from highest to lowest. The results were also analysed using the relative importance index (RII).

Current risk management practices

Respondents rated their organization's risk management practices on a 5-point Likert scale. The results reveal significant gaps in formal risk management implementation as depicted by the mean score rank values.

Table 1: Current risk management practices

S/N	Practices	Mean Score (MIS)	Standard Deviation	Level of Implementation
1	Comprehensive documented risk management procedure.	2.85	1.12	Low
2	Project risk identification at regular intervals during projects	3.15	1.08	Moderate
3	An updated Risk Register for all projects is available.	2.95	1.20	Low

4	Use of quantitative risk analysis techniques	2.45	1.15	Very Low
5	Proactive risk response planning and implementation	3.05	1.09	Moderate
6	Use of lessons learned from past projects	2.75	1.18	Low
7	Implementation of special risk management software tools.	2.35	1.22	Very Low

According to the data, risk management practices in Nigerian IT projects are mostly immature and informal. The implementation of quantitative risk analysis techniques is extremely low (MIS=2.45), as is the implementation of specialised software tools (2.35), indicating that qualitative methods, manual procedures, and no analytical methodologies are used. Moderate scores for risk identification (MIS=3.15) and response planning (MIS=3.05) indicate a basic understanding of risk management concepts, whereas low scores for formal processes (MIS=2.85) and learning from previous projects (MIS=2.75) indicate a systematic lack of institutionalising risk management practices.

ML Awareness

employing a multi-level awareness framework, which includes: Level 1: Unaware — has never heard of ML; Level 2: Aware — has heard of ML but cannot describe it; Level 3: Knowledgeable — can explain fundamental ML principles; and Level 4: Applied — has used or contemplated employing ML in project work. These were arranged using item-wise notation, such as "I can describe what Machine Learning is to a coworker.""; "I am aware of ML applications important to IT project management (e.g., predictive delay analysis, resource forecasting); "My organization has provided training on ML or AI technologies"; and "I would understand how to apply ML insights into project choices." The analysis of the awareness classification is as follows.

Table 2: Awareness classification

Awareness Level	**Frequency (n)**	**Percentage (%)**
Unaware	143	16.6
Aware (heard but cannot explain)	316	36.7
Knowledgeable (can explain)	276	32.0
Applied (used or considered)	127	14.7
Total	**862**	**100.0**

The majority of IT project managers are "Aware" or "Knowledgeable," but only 14.7% have advanced to the "Applied" level. The distribution for N = 862 is highly precise (95% CI ±3.2%), demonstrating a significant gap between awareness and practical application. To rank awareness, lists of specific ML use cases were used in conjunction with RII.

Table 3: Ranking of ML application areas by awareness

S/N	**ML Application in IT Projects**	**RII**	**Rank**	**Interpretation**
1	Predictive project delay analysis	0.61	1	High
2	Resource demand forecasting	0.54	2	Moderate
3	Automated risk scoring	0.48	3	Moderate

4	Sentiment analysis for stakeholder management	0.39	4	Low
5	AI-assisted sprint planning	0.35	5	Low

Discussion

The study's findings show that risk management techniques in Nigerian IT projects are mostly underdeveloped and informal. The adoption of quantitative risk analysis approaches was quite low (MIS=2.45), as was the use of specialised software tools (MIS=2.35). This shows that qualitative methods, manual procedures, and no analytical approaches are most commonly used. This finding is consistent with the larger issues confronting the Nigerian IT sector, where project managers frequently lack the freedom or tools to properly engage in risk management. The poor use of quantitative risk analysis approaches is especially alarming considering the complexity and uncertainty of IT projects. Nwankwo (2026) discovered that managers employ fundamental processes such as risk factor identification, impact assessment, and major risk factor management during IT project implementation, while more complex quantitative techniques are frequently underutilised.

The modest scores for risk identification (MIS=3.15) and response planning (MIS=3.05) suggest some awareness of basic risk management concepts. This finding is consistent with Singh et al. (2023), who reported that managers and team leaders had a reasonable awareness of risk management processes. However, the low scores for formal processes (MIS=2.85) and learning from previous projects (MIS=2.75) indicate a systematic failure to institutionalise risk management approaches. This lack of institutionalisation is a major concern since it implies that risk management is viewed as a project-specific activity rather than an organisational capacity. The AGP model established emphasises the significance of integrating risk management into organisational processes and culture, emphasising the human aspect as a vital factor in risk management effectiveness. The low level of machine learning awareness among IT project managers (as seen by the low MIS ratings for specialist software products) is consistent with the overall barriers to ML adoption in Nigeria's IT sector. While studies in other contexts have shown that machine learning is beneficial for risk prediction, particularly XGBoost's superior performance in capturing nonlinear correlations between risk variables, a lack of understanding and technical expertise in Nigeria remains a key impediment. According to the data, risk management practices in Nigerian IT projects are mostly immature and informal. The implementation of quantitative risk analysis techniques is extremely low (MIS=2.45), as is the implementation of specialised software tools (2.35), indicating that qualitative methods, manual procedures, and no analytical methodologies are used. This discovery is consistent with global trends, as many organisations struggle to shift from risk identification to more advanced analysis and monitoring (PMI, 2021). Moderate scores for risk identification (MIS=3.15) and response planning (MIS=3.05) indicate a basic understanding of risk management concepts, whereas low scores for formal processes (MIS=2.85) and learning from previous projects (MIS=2.75) indicate a systematic lack of institutionalising risk management practices. This supports the findings of Akinsola et al. (2020), who found a gap in the availability of adaptive systems capable of learning from past data.

Conclusions and recommendation

The study shows that risk management procedures in Nigerian IT projects are mostly underdeveloped and informal. The adoption of quantitative risk analysis approaches was extremely

low (MIS=2.45), as was the use of specialised software tools (MIS=2.35). This shows that qualitative methods, manual procedures, and no analytical approaches are most commonly used. While moderate scores for risk identification (MIS=3.15) and response planning (MIS=3.05) suggest some understanding of basic risk management concepts, low scores for formal processes (MIS=2.85) and learning from previous projects (MIS=2.75) indicate a systematic lack of institutionalised risk management practices. The recommendations below are based on the findings. They include: Because technical/technology risks are the most critical risk category, organisations should invest in technology assessment and selection processes, ensure IT system compatibility with existing infrastructure, implement robust testing and quality assurance practices, develop technology contingency plans, and hire certified IT professionals to oversee each stage of project execution. The government should create policies and programs to encourage ML adoption; provide funding and incentives for ML research and development; foster the development of ML capabilities in the IT sector; establish guidelines and standards for ML-enhanced risk management; and facilitate public-private partnerships for ML innovation. Professional organisations should incorporate adaptive risk management and ML applications into certification programs, produce CPD programs on ML-enhanced risk management, and partner with academia to create relevant training materials.

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