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Generative AI for Dynamic Risk Scenario Simulation in Project Management

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Abstract

Generative Artificial Intelligence (AI) is transforming risk management in project management by enabling dynamic, proactive, and scalable solutions to address the limitations of traditional methods. Traditional approaches often rely on static assessments, limited data utilization, and reactive mitigation strategies, which fall short in complex, rapidly evolving projects. This paper proposes a framework for leveraging generative AI models—such as Denoising Diffusion Probabilistic Models (DDPMs), Generative Adversarial Networks (GANs), transformer-based models like GPT-4, and Variational Autoencoders (VAEs)—to simulate realistic risk scenarios in real-time. These models integrate diverse data sources, including historical project data, real-time metrics, and external factors, providing a holistic view of potential risks. The benefits of generative AI include proactive risk mitigation through dynamic simulations, enhanced stakeholder communication via contextual narratives and visualizations, and scalability across projects of varying sizes and complexities. However, challenges such as data quality, model bias, and the need for human oversight must be addressed to ensure effective implementation. Future directions include multimodal AI integration, continuous improvement through reinforcement learning, and the development of ethical guidelines for responsible AI use. By addressing these challenges and leveraging its strengths, generative AI has the potential to revolutionize risk management, enabling more resilient and successful project outcomes.

Introduction

Project management, a critical discipline in modern business, involves the application of knowledge, skills, tools, and techniques to project activities to meet project requirements [1]. Risk management is a core component of project management, defined as the process of identifying, analyzing, and responding to project risks throughout the project lifecycle [1], [2]. Effective risk management is essential for ensuring project success, as it helps project teams anticipate potential issues, mitigate their impact, and maintain stakeholder confidence. However, traditional risk management approaches often fall short in dynamic, complex projects, where risks can emerge rapidly and interact in unpredictable ways [1], [3], [4]. Traditional risk management methods, such as risk matrices and historical data analysis, are often static and reactive [5]. These methods rely heavily on past experiences and expert judgment, which may not be sufficient to address the complexities of modern projects. For instance, a study by the Project Management Institute (PMI) found that 39% of projects fail due to inadequate risk management [1]. Key limitations of traditional approaches include:

- Static Risk Assessment: Traditional methods typically involve one-time risk assessments at the project initiation stage, which may not account for evolving project conditions [5]. As projects progress, new risks may emerge, and existing risks may change in likelihood or impact, but static assessments fail to capture these dynamics.

- Limited Data Utilization: While historical data is valuable, it may not provide a comprehensive view of potential risks, especially for novel or complex projects. Traditional methods often lack the capability to integrate real-time data and external factors, such as market trends or regulatory changes, into risk assessments.

- Reactive Risk Mitigation: Traditional approaches often focus on responding to risks after they have materialized, rather than proactively simulating and mitigating potential risks (PwC, 2018). This reactive mindset can lead to costly delays and resource overruns.

The advent of Artificial Intelligence (AI) has opened new possibilities for enhancing risk management in project management. Generative AI, a subfield of AI that focuses on generating synthetic data, has shown significant potential in simulating realistic risk scenarios [6]. Generative AI models, such as Generative Adversarial Networks (GANs) and transformer-based models like GPT-4 [7], can analyze vast amounts of data to generate synthetic risk scenarios that mimic real-world complexities. These models can simulate a wide range of risk factors, including resource constraints, budget overruns, and external disruptions, providing project teams with actionable insights for proactive risk mitigation. Generative AI offers several advantages over traditional risk management methods:

- Dynamic Risk Simulation: Generative AI can simulate risk scenarios in real-time, allowing project teams to anticipate and respond to evolving risks[6]. This dynamic approach enables more proactive risk management, reducing the likelihood of costly delays and overruns.
- Comprehensive Data Integration: Generative AI models can integrate diverse data sources, including historical project data, real-time metrics, and external factors such as market trends and regulatory changes. This comprehensive data integration provides a more holistic view of potential risks, enabling more accurate risk assessments.
- Proactive Risk Mitigation: By simulating a wide range of risk scenarios, generative AI enables project teams to develop proactive mitigation strategies. This proactive approach can help teams avoid potential pitfalls and ensure project success.

The primary objective of this paper is to propose a framework for using generative AI to create dynamic, customizable risk scenarios in project management. This framework aims to address the limitations of traditional risk management methods by leveraging the capabilities of generative AI to simulate realistic risk scenarios in real-time. The paper will explore the technical implementation of generative AI in risk scenario simulation, discuss the benefits and challenges of this approach, and provide recommendations for future research and practice.

Generative AI in Risk Scenario Simulation

Generative AI, a subfield of artificial intelligence, focuses on generating synthetic data that mimics real-world patterns [8]. This technology has gained significant attention due to its ability to create realistic and diverse data samples, which can be used in various applications, including risk scenario simulation in project management [9], [10]. One of the most prominent techniques in generative AI is the use of Denoising Diffusion Probabilistic Models (DDPMs), which have shown remarkable results in generating high-quality synthetic data [11]. DDPMs are a type of generative model that works by gradually removing noise from data to generate realistic samples. The process involves a forward diffusion process, where noise is added to the data over time, and a reverse diffusion process, where the noise is removed to generate the original data.

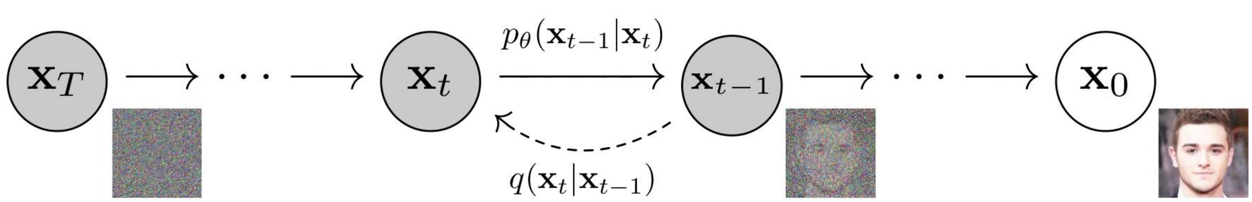

Figure 1 Illustration of a Denoising Diffusion Probabilistic Model (DDPM), showcasing the process of gradually removing noise from data to generate realistic synthetic outputs [11].

In the forward diffusion process, the data x_0 is gradually perturbed with noise over T steps, resulting in a noisy version x_T. The reverse process involves learning a model p_θ that predicts the denoised data x_{t-1} from the noisy data x_t. This process is repeated until the original data x_0 is recovered. The key advantage of DDPMs is their ability to generate high-quality synthetic data by learning the underlying data distribution [11].

Applications in Risk Scenario Simulation

Generative AI, particularly DDPMs, can be applied to risk scenario simulation in project management to address the limitations of traditional methods. By generating synthetic risk scenarios, project teams can better understand potential risks and develop proactive mitigation strategies. Here are some key applications:

Dynamic Risk Simulation: DDPMs can simulate dynamic risk scenarios by generating synthetic data that reflects the evolving nature of project risks. This allows project teams to anticipate and respond to risks in real-time, reducing the likelihood of costly delays and overruns [11].

Comprehensive Data Integration: Generative AI models can integrate diverse data sources, including Table 1. Denoising Diffusion Probabilistic Models (DDPMs) are well-suited for large-scale projects with ample data, generating highly realistic scenarios but requiring significant computational resources. Generative Adversarial Networks (GANs) provide adaptable, real-time scenario generation for structured data but may exhibit training instability and bias [13]. Transformer-based models like GPT-4 excel at creating

historical project data, real-time metrics, and external factors such as market trends and regulatory changes. This comprehensive data integration provides a more holistic view of potential risks, enabling more accurate risk assessments [6].

Proactive Risk Mitigation: By simulating a wide range of risk scenarios, generative AI enables project teams to develop proactive mitigation strategies. This proactive approach can help teams avoid potential pitfalls and ensure project success [12].

Generative AI Models for Risk Scenario Simulation

Several generative AI models can be used for risk scenario simulation, each with its own strengths and limitations that is shown in

context-aware, natural language risk narratives for stakeholder communication, though they are computationally demanding and may involve licensing costs. Variational Autoencoders (VAEs) are efficient and data-light, ideal for smaller projects, but may produce less detailed scenarios compared to GPT-4 and DDPMs.

Table 1 Comparison of Generative AI Models for Risk Scenario Simulation

Model	Data	Adaptability	Integration	Strengths	Limitations
DDPMs	High	Moderate	Moderate	Realistic scenarios; complex interactions	Intensive; large data needed
GANs	Moderate	High	High	Fast; complex dependencies handled	Unstable; potential bias
Transformers (GPT-4)	Moderate	High	Moderate	Contextual narratives; stakeholder-friendly	Licensing costs; sequential data
VAEs	Low	Low	High	Efficient; low cost	Lower quality; oversimplification

Framework and Technical Implementation

Framework for AI-Driven Risk Simulation

The framework for AI-driven risk simulation in project management is designed to address the limitations of traditional risk management methods by leveraging the capabilities of generative AI to simulate realistic and dynamic risk scenarios. This framework integrates diverse data sources, employs advanced AI models, and ensures seamless integration with existing risk management workflows.

Data Input

The foundation of AI-driven risk simulation lies in the integration of diverse and comprehensive data sources.

These data inputs can be categorized into three main types: historical project data, real-time metrics, and external factors. Historical project data includes information from past projects such as risk logs, timelines, budget variances, stakeholder feedback, and project outcomes. This data provides a baseline for identifying recurring risk patterns and trends, helping project teams understand how risks have materialized in the past and how they were mitigated. For example, a construction project's historical data might show that delays often occur during the permitting phase, allowing the team to proactively allocate more resources to this stage. Real-time metrics include current project status updates, resource utilization rates, task completion rates, sprint velocities, and other performance metrics. These metrics enable dynamic risk assessment, allowing the team to respond to evolving project conditions and emerging risks promptly. For instance, a software development project might use real-time metrics to identify that a particular sprint is falling behind schedule, prompting the team to reallocate resources or adjust priorities. External factors include market trends, regulatory changes, geopolitical events, industry-specific disruptions (e.g., supply chain issues), and other external influences. These factors can significantly impact project risks, and their integration into the risk simulation framework ensures a holistic view of potential risks. For example, a manufacturing project might incorporate market trends indicating a potential shortage of a critical raw material, prompting the team to explore alternative suppliers.

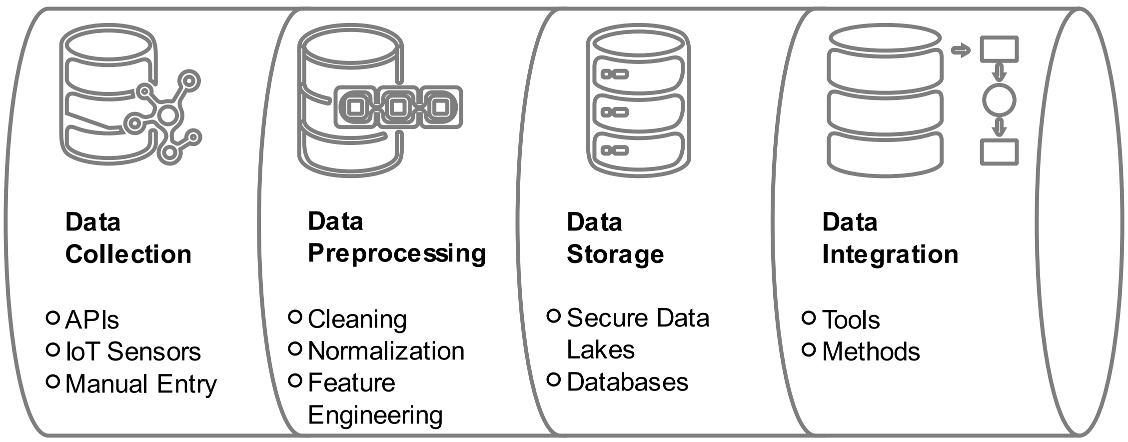

Figure 2 Dta pipeline architecture for AI-driven risk simulation

Data Pipeline Architecture

The data pipeline for AI-driven risk simulation involves several key components. Data collection is the first step, which includes using APIs to collect real-time metrics from project management tools such as Jira and Trello, IoT sensors to collect real-time data from physical assets like construction sites and manufacturing equipment, and manual entry to collect qualitative data such as stakeholder feedback and risk assessments. Data preprocessing is the next step, which involves cleaning the data by removing duplicates, handling missing values, and correcting errors. Normalization is also performed to scale data to a standard range to ensure consistent model performance. Feature engineering is another crucial step, where new features are created from raw data to improve model accuracy, such as converting qualitative risks into numerical scores.

Data storage is another important component, where large volumes of raw data are stored in secure data lakes like AWS S3 and Google BigQuery, and structured data is stored in databases such as SQL databases and NoSQL databases. Data integration is the final step, which involves using tools like Apache Kafka for streaming data and Apache Airflow for workflow orchestration. Data fusion techniques are employed to combine data from multiple sources into a unified format. Overall data pipeline is shown in Figure 2.

AI Model Training

The choice of AI model depends on the specific requirements of the project. Denoising Diffusion Probabilistic Models (DDPMs) are suitable for large-scale projects with extensive historical data, generating highly realistic risk scenarios. Generative Adversarial Networks (GANs) are suitable for mid-sized projects requiring real-time risk updates, handling complex dependencies between risk factors. Transformer-based models like GPT-4 are suitable for generating natural language risk narratives and integrating with stakeholder communications. Variational Autoencoders (VAEs) are suitable for small projects with limited historical data, providing efficient anomaly detection and data compression. The training process involves several steps. First, domain knowledge is incorporated by embedding industry-specific rules and best practices into the model. For example, in a construction project, the model might be trained to recognize that delays in the permitting phase are a common risk. Transfer learning is also used, where pre-trained models are adapted to project-specific data. For instance, a pre-trained DDPM model might be fine-tuned on historical data from similar construction projects. The training workflow includes data preparation, where data is split into training (70%), validation (20%), and test (10%) sets. The appropriate model is selected based on project requirements, such as DDPMs for large-scale projects. Hyperparameter tuning is performed using techniques like Bayesian optimization to adjust learning rates and batch sizes. Validation is done by monitoring metrics like Fréchet Inception Distance (FID) for GANs to ensure model stability.

Integration with Risk Management Workflows

The integration of AI-driven risk simulation with existing risk management workflows is crucial for effective risk mitigation. Risk scenario generation involves dynamic risk simulation, where synthetic risk scenarios are generated in real-time to reflect evolving project conditions. For example, a project team might use DDPMs to simulate the impact of a potential budget overrun on project timelines. Comprehensive data integration is also performed, where historical data, real-time metrics, and external factors are combined to create holistic risk scenarios. For instance, a project team might integrate market trends indicating a potential shortage of critical resources into their risk simulation.

Technical Implementation

Model Selection: Selecting the appropriate generative AI model for risk scenario simulation requires balancing computational efficiency, data availability, and project-specific requirements. Denoising Diffusion Probabilistic Models (DDPMs) excel in large-scale projects with extensive historical datasets (>10,000 samples), enabling the generation of high-fidelity risk scenarios that capture nonlinear interactions between variables, such as cascading delays caused by overlapping resource dependencies. However, their 1–2 week training time and computational intensity make them less suitable for agile environments. For mid-sized projects requiring real-time updates, Generative Adversarial Networks (GANs) offer faster training (3–5 days) and adaptability to structured data, such as budget fluctuations linked to supply chain volatility, but risk instability if data distributions shift abruptly. Transformer-based models like GPT-4 are ideal for stakeholder communication, generating contextual risk narratives (e.g., explaining how regulatory changes might delay compliance milestones) through fine-tuning on 500+ text samples. Variational Autoencoders (VAEs) provide a cost-effective solution for smaller projects with limited data (100–1,000 samples), though their simplified latent representations may overlook subtle correlations, such as the interplay between team morale and productivity declines.

Table 2 ***Model Selection Guide for Risk Simulation***

Model	Use Case	Training Time	Data Needs	Key Strengths	Key Limitations
DDPMs	Large-scale, data-rich projects	1–2 weeks	>10,000 samples	Captures complex, nonlinear risk dynamics	High computational cost
GANs	Real-time updates for mid-sized projects	3–5 days	1,000–10,000	Adapts to shifting data distributions	Prone to mode collapse in sparse data
GPT-4	Stakeholder-facing risk narratives	1 day	500+ text samples	Context-aware natural language generation	Licensing costs; sequential data bias
VAEs	Small projects with limited data	1–2 days	100–1,000	Efficient anomaly detection	Oversimplifies multivariate interactions

Data Privacy and Security: Ensuring data privacy is critical when integrating sensitive project data, such as stakeholder identities or proprietary metrics. Anonymization techniques like differential privacy inject controlled noise into datasets, masking personally identifiable information (PII) while preserving risk pattern integrity—e.g., obfuscating team member names without altering task delay correlations. Secure cloud environments, such as AWS SageMaker with role-based access control (RBAC), encrypt data both at rest and in transit, mitigating breaches when simulating risks like cyberattacks on project infrastructure. However, balancing privacy and utility remains challenging: over-anonymization may dilute subtle risk signals, such as geographically correlated supply chain disruptions.

Validation and Calibration: Calibrating generative AI outputs to real-world probabilities ensures actionable risk insights. Brier scores quantify the accuracy of probabilistic risk forecasts (e.g., predicting a 70% likelihood of budget overruns), while reliability diagrams visualize gaps between predicted and observed frequencies. Backtesting against historical outcomes reveals systemic biases—for instance, a model may underestimate permit approval delays due to unaccounted regulatory lags in training data. A iterative calibration workflow refines these outputs:

Generate synthetic risks: DDPMs simulate scenarios like equipment failures cascading into timeline overruns.

Validate against historical data: Compare synthetic delays with past project logs to identify over/underestimation trends.

Adjust model parameters: Reduce calibration error by retraining on reweighted datasets that amplify underrepresented risks, such as rare but high-impact geopolitical disruptions.

Complex Dynamics and Correlations: Generative AI must account for nonlinear interactions, such as the compounding effect of vendor delays and workforce shortages on critical path tasks. For example, a 10% delay in material delivery (simulated via GANs) might linearly extend timelines by 5 days, but concurrent strikes (modeled via DDPMs) could amplify this to 15 days due to rescheduling bottlenecks. Similarly, transformer models can correlate external factors like interest rate hikes with increased stakeholder anxiety, indirectly affecting approval cycles. These dynamics necessitate hybrid approaches—e.g., coupling VAEs for anomaly detection with GPT-4 to explain how a singular risk event (e.g., a data breach) propagates across technical, financial, and reputational dimensions.

Table 3 ***Calibration Metrics and Outcomes***

Metric	Purpose	Model Application	Outcome Example
Brier Score	Quantify probabilistic forecast accuracy	GANs (budget risks)	Reduced from 0.25 to 0.12 post-calibration
Reliability Diagram	Visualize prediction-reality alignment	DDPMs (timeline risks)	90% of scenarios within 5% error margin
F1 Score	Balance precision/recall of risk detection	VAEs (anomalies)	Improved from 0.68 to 0.82 with retraining
KL Divergence	Measure data distribution alignment	GPT-4 (narrative logic)	Divergence < 0.05 after domain adaptation

Benefits and Challenges of Generative AI in Risk Scenario Simulation for Project Management

The integration of generative artificial intelligence (AI) into risk scenario simulation represents a transformative leap in project management. By leveraging advanced models such as Denoising Diffusion Probabilistic Models (DDPMs), Generative Adversarial Networks (GANs), transformer-based models like GPT-4, and Variational Autoencoders (VAEs), project teams can address the limitations of traditional risk management methods while unlocking new opportunities for proactive decision-making. However, alongside its numerous benefits, this approach also introduces challenges that must be carefully managed to ensure its successful implementation. This section explores the key advantages and potential hurdles of using generative AI for dynamic risk scenario simulation.

Benefits and Challenges

Generative AI is revolutionizing risk management in project management by enabling dynamic, proactive, and scalable solutions. It leverages advanced models such as Denoising Diffusion Probabilistic Models (DDPMs), Generative Adversarial Networks (GANs), transformer-based models like GPT-4, and Variational Autoencoders (VAEs) to simulate realistic scenarios, integrate diverse data sources, and provide actionable insights.

Benefits of Generative AI

Proactive Risk Mitigation: Traditional risk management methods are often static and reactive, leaving teams unprepared for emerging risks. In contrast, generative AI enables proactive risk mitigation by simulating dynamic scenarios that evolve alongside project conditions. For example, DDPMs can generate synthetic data to predict how resource constraints or budget overruns might unfold over time, allowing teams to anticipate and address these issues before they materialize. Additionally, GANs can model the cascading effects of interdependent risks, such as delays in material delivery causing broader timeline disruptions. This foresight empowers organizations to develop targeted strategies that address root causes rather than symptoms, enhancing project resilience.

Enhanced Stakeholder Communication: Effective communication is crucial for maintaining stakeholder confidence. Generative AI improves this through visualized scenarios and transparent reporting. Transformer-based models like GPT-4 excel at generating natural language narratives, helping stakeholders understand complex risks without requiring technical expertise. For instance, GPT-4 can explain how regulatory changes might impact compliance milestones. Visualizations created using DDPMs further enhance understanding by illustrating the ripple effects of risks, such as permitting delays affecting timelines and budgets. These tools foster transparency and trust, enabling informed decision-making.

Scalability and Customization: Unlike traditional methods, generative AI adapts to projects of all sizes and complexities. DDPMs suit large-scale projects with extensive historical data, while GANs cater to mid-sized projects requiring real-time updates. VAEs provide cost-effective solutions for smaller projects with limited data. The ability to customize simulations ensures alignment with specific project priorities. For example, a manufacturing project might focus on supply chain disruptions, whereas a software development project might emphasize sprint velocity. This flexibility maximizes the utility and impact of generative AI across diverse contexts.

Challenges and Mitigation Strategies

Despite its advantages, implementing generative AI poses challenges.

Data Quality and Availability: These models require vast amounts of high-quality data, but organizations often face issues with sparse or biased historical records. Poor-quality data can lead to incomplete or misleading insights. To mitigate this, organizations should invest in robust data collection practices, leveraging IoT sensors and APIs for real-time metrics. Techniques like differential privacy can protect sensitive information while preserving data integrity.

Model Bias and Fairness: Biases in training data can propagate into simulations, undermining credibility and leading to unfair decisions. Organizations must incorporate fairness-aware algorithms during training, such as adversarial debiasing, and involve diverse teams in validation processes. Regular audits and recalibrations ensure long-term fairness.

Human Oversight: While AI excels at analyzing data, it lacks contextual understanding and ethical judgment. Human oversight is essential to validate outputs and guide decision-making. Project managers should review AI-generated insights, provide feedback, and make final decisions based on both quantitative and qualitative considerations. Collaborative platforms integrating AI outputs with human inputs ensure synergy between technology and expertise.

Conclusion and Future Directions

Generative AI has emerged as a powerful tool for revolutionizing risk management in project management. By simulating dynamic, customizable risk scenarios, it addresses the limitations of traditional methods, which often rely on static assessments and limited data utilization. The ability to integrate diverse data sources—ranging from historical project logs to real-time metrics and external factors—provides a holistic view of potential risks, enabling more accurate and timely responses. Furthermore, generative AI enhances stakeholder communication through visualized scenarios and transparent reporting, fostering trust and alignment among all parties involved. The benefits of generative AI extend beyond mere risk identification; it empowers project teams to adopt a proactive stance toward risk mitigation. By anticipating and addressing risks before they escalate, organizations can minimize delays, avoid cost overruns, and ensure smoother project execution. Additionally, the scalability and customization capabilities of generative AI make it adaptable to projects of varying sizes and complexities, ensuring broad applicability across industries. From large-scale infrastructure developments to agile software sprints, generative AI offers tailored solutions that align with specific project requirements.

However, realizing the full potential of generative AI requires addressing several challenges. Issues related to data quality, model bias, and the need for human oversight highlight the importance of thoughtful implementation and ongoing refinement. Organizations must invest in robust data pipelines, fairness-aware algorithms, and collaborative workflows to maximize the value of AI-driven risk simulation. When these challenges are effectively managed, generative AI stands poised to transform risk management into a dynamic, forward-looking discipline that drives project success.

Future Directions

Looking ahead, several promising avenues exist for advancing the role of generative AI in risk scenario simulation. These future directions aim to further enhance the technology's capabilities, refine its applications, and ensure ethical and responsible use.

1. Multimodal AI: Combining Text, Data Visualizations, and Synthetic Scenarios

- Use NLP and computer vision to enhance contextual understanding and visualization clarity.
- Explore AR/VR technologies for immersive stakeholder experiences of simulated risks.

2. AI-Driven Continuous Improvement: Refining Simulations Based on Project Outcomes

- Apply reinforcement learning for adaptive model evolution.
- Benchmark simulations against industry standards to ensure accuracy and trustworthiness.

3. Ethical Guidelines: Transparency, Accountability, and Human-AI Collaboration

- Ensure transparency by clearly explaining model operations, data usage, and decision-making processes.
- Establish accountability through ethics boards, regular audits, and mechanisms to address biases or errors.

- Collaborate across academia, industry, and regulators to create shared ethical frameworks for responsible AI use.

These directions aim to enhance generative AI's capabilities, refine its applications, and ensure ethical, responsible integration into risk management.

Reference

[1] K. H. Rose, "A guide to the project management body of knowledge (PMBOK guide) fifth edition," *Proj. Manage. J.*, vol. 44, no. 3, pp. e1–e1, Jun. 2013.

[2] C. Reviews, *A guide to the project management body of knowledge*, 4th ed. La Vergne, TN: Cram101, 2017.

[3] K. Bainey, *AI-driven project management*. Nashville, TN: John Wiley & Sons, 2024.

[4] J. Geraldi, G. Locatelli, G. Dei, J. Söderlund, and S. Clegg, "AI for management and organization research: Examples and reflections from project studies," *Proj. Manage. J.*, vol. 55, no. 4, pp. 339–351, Aug. 2024.

[5] M. S. Sharbaf, "Artificial intelligence in Germany:," in *International Perspectives on Artificial Intelligence*, Anthem Press, 2022, pp. 33–42.

[6] I. J. Goodfellow *et al.*, "Generative Adversarial Networks," *arXiv [stat.ML]*, 10-Jun-2014.

[7] [Online]. Available: https://openai.com/index/gpt-4-research/. [Accessed: 06-Feb-2025].

[8] J. Yao, B. Zhang, D. Wang, D. Lei, and R. Tong, "Risk coupling analysis under accident scenario evolution: A methodological construct and application," *Risk Anal.*, vol. 44, no. 6, pp. 1482–1497, Jun. 2024.

[9] E. Firuzi, A. Ansari, K. Amini Hosseini, and N. Kheirkhah, "Developing an earthquake damaged-based multi-severity casualty method by using Monte Carlo simulation and fuzzy logic; case study: Mosha fault seismic scenario, Tehran, Iran," *Stoch. Environ. Res. Risk Assess.*, Feb. 2024.

[10] D. Rosen and D. Saunders, "Regress under stress: A simple least-squares method for integrating economic scenarios with risk simulations," *J. Risk Manag. Financ. Inst.*, vol. 9, no. 4, p. 391, Oct. 2016.

[11] J. Ho, A. Jain, and P. Abbeel, "Denoising Diffusion Probabilistic Models," *arXiv [cs.LG]*, 19-Jun-2020.

[12] D. P. Kingma and M. Welling, "Auto-Encoding Variational Bayes," *arXiv [stat.ML]*, 20-Dec-2013.

[13] Y.-L. Du, C.-H. Ma, Y.-F. Liao, L. Wang, Y. Zhang, and G. Niu, "Is clinical scenario simulation teaching effective in cultivating the competency of nursing students to recognize and assess the risk of pressure ulcers?," *Risk Manag. Healthc. Policy*, vol. 14, pp. 2887–2896, Jul. 2021.