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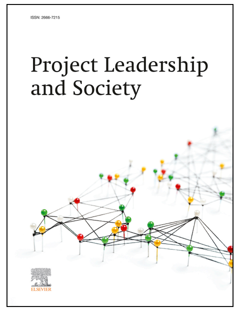

A GenAI-driven risk management framework for sustainable development projects

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A GenAI-driven risk management framework for sustainable development projects

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A Generative Artificial Intelligence (GenAI)–Driven Risk Management Framework for Sustainable Development Projects

Abstract

The purpose of this study is to develop a framework that identifies the drivers, challenges, and benefits of integrating Generative AI (GenAI)–driven risk management into sustainable development projects. To achieve this aim, a systematic literature review was conducted, analysing 66 articles on GenAI applications in project risk management published in leading academic journals between 2014 and 2024. The findings indicate that integrating GenAI into risk management enhances sustainability performance by improving environmental, social, and economic outcomes. This contribution is reflected in mechanism-level improvements across the risk management process, including earlier risk identification and prediction, faster interpretation of unstructured project data, and enhanced decision support. These capabilities reduce rework and material waste, strengthen safety and quality management, and improve regulatory traceability and cost efficiency. GenAI also supports more accurate risk forecasting, resource optimisation, and compliance monitoring, enabling project teams to address sustainability challenges more proactively. Despite these benefits, several barriers limit widespread adoption, including technical constraints, legal and regulatory uncertainty, ethical concerns, organisational readiness issues, and resource limitations. The review further highlights that sustainability gains depend on data quality, system transparency, and effective human oversight, as weak governance may introduce bias and reduce decision reliability. The proposed framework provides a structured approach to overcoming these challenges, promoting effective and sustainable GenAI-driven risk management in sustainable development projects. The framework serves as a roadmap for organisations seeking to balance innovation with sustainability in project risk management practices during the era of digital transformation.

Keywords: Generative AI; GenAI; Project Management; Risk management; Sustainable Development.

1. Introduction

The transition to Industry 4.0 has introduced technologies aimed at human empowerment and a deeper understanding of corporate culture and risk (Dacre et al., 2024; Al Naqbi et al., 2025). Among these innovations, AI has become a critical tool, influencing sectors with significant project management activity such as engineering, construction, management, and manufacturing (Golovianko et al., 2023; Mohamed et al., 2024). In these domains, AI has shaped sustainable development, profitability, and responses to social demands (Dwivedi et al., 2021). In this context, project organisations are increasingly required to manage digital-transformation risks while simultaneously delivering measurable sustainability outcomes, making risk management the practical bridge between Industry 4.0 capabilities and sustainable project delivery (Podgorska, 2022). Accordingly, this paper focuses specifically on GenAI-driven risk management rather than AI adoption in general and its implications for sustainable development projects.

AI can be broadly divided into traditional AI and Generative AI (GenAI), based on methods, techniques, models, and applications (Smith and Wong, 2022). Traditional AI relies on predetermined rules and classical machine learning techniques to solve well-defined problems (Gonzalez and Hernandez, 2018; Al-Saffar et al., 2024). Examples include expert systems, decision trees, and linear regression, which perform effectively when objectives and problem spaces are clear (Minh et al., 2022; Erickson, 2021). However, such systems cannot generate new content and remain constrained by their programmed scope. Early AI applications, such as rule-based diagnostic tools and financial forecasting models, illustrate these limitations (Shadbolt, 2022; Sung et al., 2020). As Craig et al. (2024) observe, they were designed to handle narrow, predefined tasks. GenAI emerged to overcome these constraints.

GenAI refers to models capable of generating new content, text, images, audio, or code, by learning from existing data and producing outputs that resemble it (Chenya et al., 2022; Dulam et al., 2023). These models rely on advanced deep learning, with Generative Adversarial Networks (GANs) and Transformer architectures such as ChatGPT among the most prominent (Baduge et al., 2023; Gonzalez and Hernandez, 2018). According to Gil et al. (2024), GenAI produces content often indistinguishable from that created by humans, significantly expanding AI's ability to learn, solve problems, analyse contexts, and respond logically. Other approaches, including variational autoencoders (VAEs) and diffusion models, further broaden its applications, generating realistic text, images, and even molecular structures (Celik and Eltawil, 2024; Bengesi et al., 2024). Developing GenAI systems requires careful design: setting objectives, collecting and preprocessing data, selecting model architectures, and optimising hyperparameters during training (Falkner et al., 2018; Holtzman et al., 2019).

In project management, GenAI is already enhancing scheduling, cost control, communication, scope definition, quality assurance, stakeholder engagement, and risk management (Regona et al., 2022; Pan and Zhang, 2021). Risk management is particularly important given the uncertainty of large-scale projects (Al-Mhdawi et al., 2023). Traditional approaches, largely based on human judgment, are constrained by cognitive bias, limited time, and data complexity (Khodabakhshian et al., 2023; Al-Mhdawi et al., 2024a). GenAI addresses these challenges by strengthening risk identification, assessment, decision-making, and monitoring (Al-Mhdawi et al., 2023; Aramali et al., 2025). However, prior studies also report that these benefits are context-dependent and can be undermined through issues such as low-quality project data, limited transparency, and over-reliance on automated outputs factors that are especially critical in high-stakes sustainability decisions(Pan and Zhang, 2021).

Different GenAI models offer complementary benefits. GANs generate synthetic data and simulate diverse scenarios, aiding risk detection; VAEs support anomaly detection and the identification of emerging risks (Cont et al., 2022; Moon et al., 2023). Transformer models, such as GPT and BERT, analyse complex datasets, including contractual and project documentation, to reveal hidden risks (Zou et al., 2017; Jafari et al., 2021). Diffusion models capture uncertainty by generating probabilistic outcomes (Gholizadeh et al., 2018), while Reinforcement Learning (RL) optimises decision-making in resource allocation and scheduling under uncertainty (Akinosho et al., 2020). Collectively, these approaches improve the prediction of risk probability and impact, while enabling more resilient response strategies (Mohamed et al., 2024). As Nishant et al. (2020) note, GenAI not only mitigates risks but also fosters innovation by supporting adaptive and robust project planning.

In 1992, the United Nations (UN) formally adopted the principle of sustainable development, a commitment reinforced in 2015 with the introduction of the Sustainable Development Goals (SDGs) (Galvao et al., 2016). This global agenda has reshaped project delivery, particularly project risk management, by requiring the identification of risks linked to environmental, social, and economic factors (Taneja et al., 2022; Tiza, 2022). Given the uncertainty and complexity of decision-making in this context, GenAI has been proposed as a promising tool for enhancing risk assessment and management in sustainable projects (Al-Saffar et al., 2024; Kar et al., 2022). In this paper, sustainable development projects are defined as projects whose intended outcomes explicitly contribute to sustainable development and the SDGs, such as low-carbon infrastructure, resource-efficient buildings, renewable energy systems, or initiatives with explicit environmental and social development objectives. By contrast, sustainable project management (SPM) refers to the management approach used to plan, govern, and deliver projects while integrating environmental, social, and economic considerations into decision making and control. Accordingly, this study focuses on GenAI-driven risk management within sustainable development projects, with sustainable project management treated as the delivery lens through which such projects are managed.

In delivering sustainable development projects, sustainable project management (SPM) seeks to minimise environmental impacts, preserve resources, and promote community well-being through practices such as waste reduction, resource optimisation, and material reuse (Tiza, 2022). Beyond ecological preservation, sustainability can deliver broader benefits, including higher productivity, improved quality of life, and reduced costs (Ibrahim, 2016). It prioritises long-term societal welfare over short-term profit (Kiani et al., 2021). Effective implementation requires early stakeholder engagement, with attention to energy efficiency, material selection, waste management, and sustainable design (Kiani et al., 2021). Sustainability encompasses ecological, economic, and social dimensions, addressing cost control, health and safety, and community needs (Braganca et al., 2014; Zavadskas et al., 2018). This holistic approach integrates environmental protection, economic stability, and social equity (Karakhan et al., 2017). However, it also adds complexity, as projects must manage environmental and social impacts while balancing economic growth (Gibson, 2006). Robust risk management strategies are therefore essential to ensure long-term project viability by aligning economic, environmental, and social sustainability goals (Adewale et al., 2024; Behrooz et al., 2023). At the same time, GenAI is not inherently sustainable. Energy-intensive computation, data privacy risks, and algorithmic bias can generate environmental and social trade-offs when governance and assurance are weak(Dua, and Patel, 2024). This tension between promised efficiency gains and potential sustainability costs should be made explicit when positioning GenAI within sustainable project risk management.

The literature on GenAI in project risk management provides a useful starting point, though gaps remain. Chenya et al. (2022) and Yaseen et al. (2020) examined trends in intelligent risk management but did not consider sustainable development or the balance of GenAI's challenges and benefits. Regona et al. (2023) studied GenAI in sustainable projects, though with a focus on general management rather than risk management specifically. Al-Mhdawi et al. (2023) explored GenAI-driven risk management and identified areas for improvement, but their findings may not fully extend to sustainable projects, where decisions often involve complex trade-offs across environmental, social, and economic dimensions. Notably, the literature does not fully agree on GenAI's effectiveness or its net sustainability contribution. While some studies report improved speed and broader coverage in risk identification, others emphasise risks such as hallucination, accountability gaps, and ethical trade-offs that can undermine decision quality and weaken sustainability outcomes. In addition, although GenAI is relevant across many industries, this review is intentionally scoped to the construction sector because it is highly project-based, and sustainability considerations are central to construction project delivery and governance.

Building on this body of work, the present research addresses these gaps by linking studies on GenAI's challenges and benefits in risk management to the growing trend of sustainable projects. It proposes a framework connecting the drivers of GenAI adoption in sustainable project risk management to its associated challenges and benefits, viewed through the lens of sustainable development. Therefore, the research problem addressed in this paper is the absence of an integrated, risk-focused synthesis that (i) consolidates the reported sustainability-related impacts of GenAI-driven risk management in sustainable development projects and (ii) explains the key drivers and challenges that shape adoption and influence those impacts. This need has become particularly urgent following the rapid expansion of accessible large language models, where adoption has outpaced organisational governance and left sustainable project managers uncertain about safe and effective implementation. Bringing together risk management, sustainability triple-bottom-line, and AI governance/ethics considerations, the study responds to an emerging academic and practical need for integrated frameworks rather than technology-led assumptions. The following research questions are posed to address these gaps and to provide timely guidance for both researchers and practitioners. Accordingly, this research seeks to answer two key questions that are examined in the context of sustainable development projects within the construction sector.

Q1: How does the use of GenAI-driven risk management impact sustainable development projects?

Q2: What are the challenges, drivers, and impacts associated with the adoption of GenAI in project risk management for sustainable development projects?

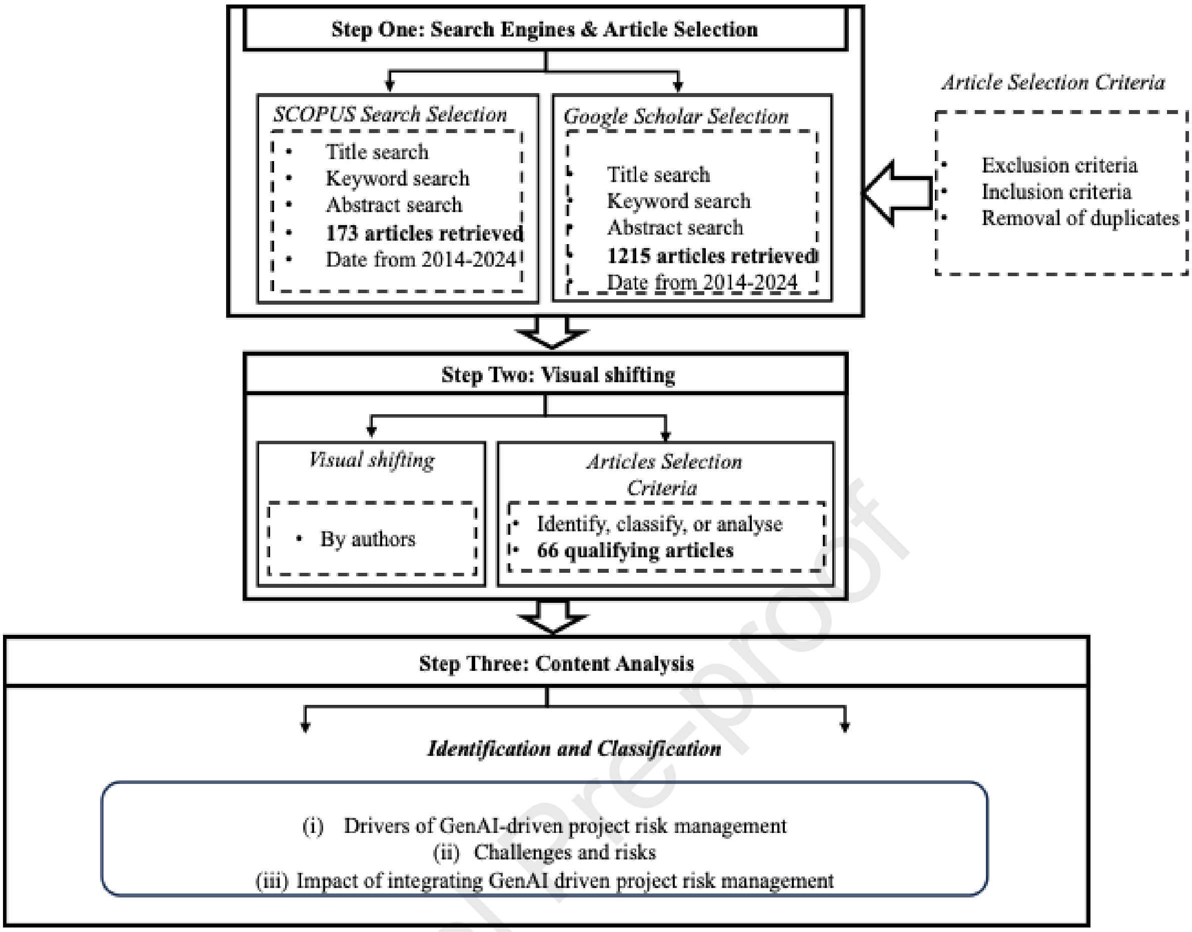
To address these questions, the authors applied the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology to identify the drivers, challenges, and benefits of implementing GenAI-driven project risk management in sustainable projects. Following the stages of identification, screening, and eligibility, a framework was developed to illustrate the interrelationships among these elements, thereby offering a comprehensive perspective. The remainder of the paper is structured as follows: Section 2 outlines the research methodology. Section 3 presents the results and discusses the key findings. Finally, Section 4 provides the conclusions, highlights the study's limitations, and suggests directions for future research.

2.0 Methodology

In this research, the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework was adopted to ensure a rigorous and transparent methodology for conducting the Systematic Literature Review (SLR). PRISMA is widely recognised as a highly effective standard across disciplines, including project management, due to its structured and comprehensive approach to synthesising research findings (Tumpa et al., 2024; Almashhour et al., 2025; Papadonikolaki et al., 2025; Székely et al., 2025; Elseknidy et al., 2025a,b; Al-Mhdawi et al., 2026). It provides a clear protocol for systematically searching, screening, evaluating, and synthesising data (Howard et al., 2017), which aligns closely with the research objectives of identifying the drivers, challenges, and benefits of GenAI-driven risk management in sustainable development projects.

In this study, PRISMA was applied as an operational protocol to structure and report the review. Specifically, it informed database selection and search execution, duplicate removal, title and abstract screening followed by full-text eligibility assessment using predefined criteria in Tables 1–2, and transparent reporting of the selection process as shown in Figure 1. To strengthen methodological reflexivity, we piloted the initial search and screening on a subset of records and refined the protocol to reduce false positives, such as studies discussing AI in general without an explicit GenAI-driven risk-management focus, while maintaining coverage of sustainability and risk-management concepts. This refinement was necessary because GenAI terminology is used inconsistently and many AI studies address project analytics without targeting GenAI-enabled risk workflows; accordingly, the final protocol balances breadth and specificity by retaining only studies that contribute explicitly to GenAI-driven risk management. PRISMA's emphasis on rigour and transparency, supported by its checklist and flowchart, strengthens reliability and reproducibility (Trifu et al., 2022; Rezvani et al., 2023). It has also been used in closely related reviews (Nyoto et al., 2024; Dacre et al., 2024; Wach et al., 2023), supporting its suitability here. The following subsections outline each stage of the adopted PRISMA approach, with the criteria detailed in Tables 1–2 and the selection flow summarised in Figure 1.

Figure 1. *PRISMA review process.*



2.1 Identification

We conducted a comprehensive search across two major electronic databases, SCOPUS and Google Scholar, to examine the impacts, drivers, and challenges of implementing GenAI-driven risk management in sustainable development projects. Given that construction is considered one of the most '*projectised'* industries, characterised by unique and temporary endeavours (Cooke-Davies and Arzymanow, 2003; Grant and Pennypacker, 2006), our analysis focused specifically on sustainable projects in construction. As Stanitsas et al. (2021) notes, "*sustainability concepts showcase significant value in construction projects*" (p. 1).

The keyword strategy balanced breadth in capturing sustainability and risk-management literature with specificity in retaining only studies that explicitly address GenAI-enabled risk management. "Generative AI" served as the anchor term to distinguish GenAI-driven approaches from broader AI analytics and conventional predictive modelling. Broad terms such as "machine learning" and "deep learning" were not made mandatory because pilot searches showed they substantially increased retrieval of general AI studies without an explicit GenAI–risk management linkage; such studies were therefore included only if returned by the query and eligible at screening. "AI ethics" was not compulsory because it retrieves large volumes of governance literature often disconnected from project risk management, so ethical and legal issues were captured through screening and coded during synthesis. Finally, "construction" was required as a deliberate domain boundary aligned with the study objective; we acknowledge this may exclude other sectors and therefore position the framework as construction-grounded, with cross-sector replication and validation proposed for future research.

The selection of search terms was guided by prior literature on Generative AI, project risk management, and sustainability (e.g., Al-Mhdawi et al., 2024b; Waqar et al., 2023; Yigitcanlar et al., 2020; Smith & Wong, 2022), ensuring a systematic and reproducible approach. Key terms included '*Generative AI*', '*Projects*', '*Project Management*', '*Construction*', '*Risk Management*', and '*Sustainable Development*', along with the three focal aspects of GenAI-driven risk management: '*impact*', '*drivers*', and '*challenges*'.

For the search on SCOPUS, we adopted the following Boolean search string:

TITLE-ABS-KEY ('Generative AI' AND 'Projects' AND 'Construction' AND 'Risk Management' AND ('Sustainable Development' OR 'Environmental Sustainability' OR 'Societal Sustainability' OR 'Economic Sustainability')) AND (LIMIT-TO (LANGUAGE, 'English')) AND (LIMIT-TO (SRCTYPE, "j"& "c")) AND (PUBYEAR > 2014 AND PUBYEAR < 2024).

For the search on Google Scholar, we refined the search to focus on credible sources by using:

'Generative AI' AND 'Projects' AND 'Construction' AND 'Risk Management' AND ('Sustainable Development' OR 'Environmental Sustainability' OR 'Societal Sustainability' OR 'Economic Sustainability') site:*sciencedirect.com* OR site:*springer.com* OR site:*ascelibrary.org*

This prioritised publications from well-established academic publishers. We excluded studies that lacked a direct focus on GenAI-driven risk management, non-peer-reviewed sources (e.g., blogs, editorials, preprints), and duplicates across databases. This structured approach ensured both transparency and rigour in identifying relevant literature.

We selected 2014 as the starting point to capture developments over the past decade. Although Generative AI has roots dating back to 1985, initially applied in content generation, image processing, and engineering (Gupta et al., 2024), its rapid expansion has been driven by advances in neural network architectures, computing power, and large datasets (Leslie & Rossi, 2023). This period also reflects the growing influence of GenAI on projects, particularly with the emergence of sophisticated models for text and image generation (Wang, 2023).

2.2 Screening

The screening phase of systematic reviews entails evaluating large volumes of literature to identify studies relevant to the research focus (Howard et al., 2020). Researchers have explored several approaches to automate this process, including active learning and integrated recall estimation (Adeva et al., 2014). Some methods prioritise identifying irrelevant studies with high precision to achieve near-perfect recall of relevant ones (Abilio et al., 2015).

In this study, we examined the titles, keywords, and abstracts of articles published between 2014 and 2024 to ensure an accurate and efficient selection process. To strengthen reliability, the initial selection was cross-checked by co-authors, who validated the suitability of the included studies. Additionally, to reduce subjectivity, screening decisions were independently cross-checked by two authors using the predefined inclusion/exclusion rules (Tables 1 and 2). Discrepancies were discussed and resolved through consensus, with third-author adjudication where required. Although a formal κ statistic was not calculated, the independent checking and adjudication process provides transparency and reduces reviewer bias in determining whether studies explicitly addressed GenAI-driven risk management.

Following PRISMA guidelines, we applied a transparent and systematic procedure, carefully documenting the number of articles excluded at each stage based on explicit criteria. This rigorous screening ensured that only literature directly addressing our research questions was retained, providing a clear and focused foundation for the review.

2.3 Eligibility

The eligibility stage in PRISMA involves defining the criteria for including or excluding studies, which should be clearly reported in the structured summary of a systematic review (Moher et al., 2010). This stage is critical for ensuring the transparency and reproducibility of the review process (Brennan & Munn, 2021).

Following the screening phase, we conducted a thorough evaluation of each publication's eligibility through a full-text review, guided by predefined Eligibility Criteria (*EC*) summarised in Table 1.

EC1 excluded articles where full-text access was unavailable, either due to high cost or restrictive access requirements, such as institutional logins, which limit availability for independent researchers. *EC2* excluded articles that mentioned GenAI or risk management only in passing, as a keyword, example, or cited fact, without substantive relevance to the research questions. This included papers that briefly referenced GenAI without analysing its role in risk management, data analytics, or decision-making. *EC3* excluded articles discussing GenAI or risk management solely in terms of research trends or recommendations, without conducting in-depth investigation. Finally, *EC4* excluded articles not focused on the construction sector, in line with our earlier observation regarding the significant value of sustainability in construction projects (Stanitsas et al., 2021).

This rigorous eligibility assessment ensured that only studies directly relevant to GenAI-driven risk management in sustainable construction projects were retained for detailed analysis.

Table 1. Summary Eligibility criteria

Code	Eligibility criteria
EC1	Full-text not available
EC2	GenAI or Risk management is only used as a keyword, example, fact or cited expression.
EC3	GenAI or Risk management is only used to describe research trends or recommendations.
EC4	The research does not focus on the construction sector.

2.4 Inclusion

The inclusion process in systematic reviews is often rigorous, with studies reporting high exclusion rates from initial search results (Rajaguru et al., 2022; Taneja et al., 2022). Inclusion criteria typically prioritise peer-reviewed, full-text articles in English that address specific interventions or frameworks relevant to the research question (Silva et al., 2024).

In this study, we required that papers explicitly examine GenAI and project risk management in construction or have these topics as their primary research focus. This ensured that only articles directly aligned with our research objectives were considered. Table 2 summarises the Inclusion Criteria (*IC*) developed for this review:

IC1: Papers must present results based on experiments using any GenAI model (e.g., BNN or GPT) or derive conclusions from review papers published in reputable journals or conferences. *IC2*: Articles must provide evidence of the impacts or challenges of GenAI on all or part of the risk management process. Finally, *IC3*: GenAI-driven project risk management must be central to the study's objectives, rather than addressed tangentially.

Applying these criteria resulted in a final set of 66 articles selected for review. A detailed overview of these articles, including their source types and relevance, is provided in Appendix A. This phase was pivotal in finalising the selection of studies for our systematic analysis.

Table 2. Inclusion criteria

Code	Inclusion Criteria
IC1	Impacts of GenAI driven risk management results based on experimental validation or credible review Criterion
IC2	The research shows the impacts of GenAI overall or part of CRM.
IC3	GenAI and risk management are part of the main research effort.

3. Results and Discussion

3.1 Year-by-year analysis of the number of articles published.

In this study, we conducted an annual publication analysis to identify trends and patterns in research on GenAI-driven risk management applications in sustainable development projects. This analysis examines the number of articles published each year, providing insights into the evolution, knowledge accumulation, and maturation of the topic over time (Ma and Lund, 2020).

To perform this analysis, we applied the inclusion criteria outlined in the first step of our methodology to select appropriate journals and conferences. Using keywords, titles, and selection criteria described in the second step, we initially identified 398 papers related to GenAI-driven risk management in sustainable development published between 2014 and 2024.

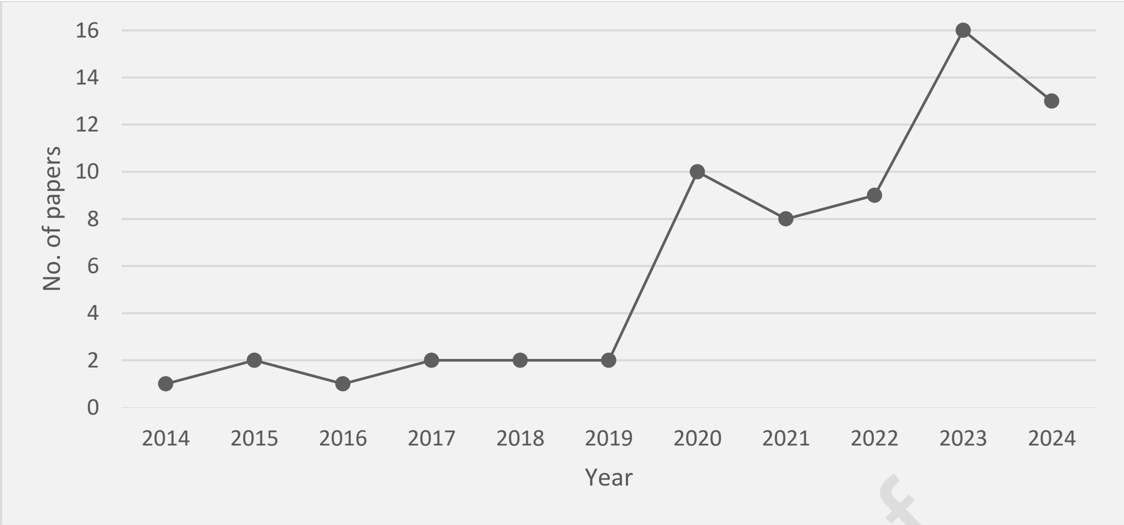
The papers were then rigorously screened based on titles and abstracts for relevance and consistency. Following a comprehensive full-text review, only 66 articles were found to thoroughly address the drivers, challenges, and impacts of GenAI-driven risk management in sustainable development projects.

As summarised in Table 3, 15.15% of these studies were published between 2014 and 2019, while 84.85% appeared between 2020 and 2024, indicating a marked increase in research interest. Figure 2 further illustrates this trend, showing the annual publication frequency from 2014 to 2024. The figure reveals a steady increase in publications over the years, culminating in near-exponential growth starting in 2023, reflecting the rising prominence of GenAI in sustainable project risk management research. Therefore, the growth in publications indicates a rapidly evolving and still-maturing field, where conceptual development is outpacing consolidated evidence on implementation outcomes. This trend suggests that organisations are experimenting with GenAI for risk tasks, but the research base remains fragmented across use-cases, data types, and assurance practices. For sustainable project risk management, this implies that clear governance, validation, and decision-accountability mechanisms are likely to be decisive factors in whether GenAI adoption translates into measurable environmental, social, and economic benefits rather than producing unintended risk.

Table 3. Number of articles in year range

Period	Papers	No. of papers	percentage
2014 - 2019	Zhang et al., (2014), Costantino (2015), Najafabadi et al., (2015), Kulkarni et al. (2017), Wu et al. (2017), Zou et al. (2017), Poh et al. (2018), Parveen (2018), Lytras and Chui (2019), Mrowczyńska et al., (2019)	10	15.15%
2020 - 2024	Pillai and Matus (2020), Yaseen et al. (2020),Truby (2020), Yigitcanlar et al., (2020), Goralski and Tan (2020),Zhang et al., (2020), Wu and Shang (2020), Eber (2020), Akinosho et al., (2020), Boughaba, and Bouabaz (2020), Abioye et al. (2021), Hannan et al., (2021), Liengpunsakul (2021), Pan and Zhang (2021), Afzal et al. (2021), Choi, et al. (2021), An et al. (2021), Manzoor et al., (2021), Regona et al. (2022), Li et al., (2022), Liao et al., (2022), Smith and Wong (2022), Baduge et al., (2022), Kar et al., (2022), Olanrewaju (2022), Erfani and Cui (2022), McMillan and Varga (2022), Aladag (2023),Turek et al., (2023),Waqar et al., (2023), Singh et al., (2023), Gupta et al., (2023), Saka et al., (2023), Mishra et al., (2023), Bandi et al., (2023), Fridgeirsson et al., (2023), Chenya et al., (2023),Jallow et al., (2023), Kazeem et al (2023), Hashfi and Raharjo (2023), Giraud et al., (2023), Behrooz et al., (2023), Boinot et al., (2023), Liang et al., (2024), Chou et al., (2024), Adewale et al., (2024), Al-Saffar et al., (2024), Greif et al., (2024), Metwally et al., (2024), Muller et al., (2024), Nyqvist et al., (2024), Strube et al., (2024),Uriarte et al., (2024), Wankhede et al., (2024), Zhou et al., (2024), Regona et al., (2024)	56	84.85%

Figure 2. Publication trends from 2014 to 2024



3.2 Keyword analyses occurrences and relationship

Keyword analysis is a valuable method for examining research trends and topics in scientific literature (Lakhanpal et al., 2014). Frequency analysis of keywords can also generate keyword clouds, visually representing the prominence of specific topics (Maki and Webster, 2018). Decker et al. (2007) proposed a text mining approach that analyses titles and abstracts using a semantics-based method to detect emerging research trends and early-stage researchers. Similarly, Le et al. (2014) explored trends in information systems research by analysing keywords from top journals, revealing frequently used terms and patterns over time.

In this study, the most common keywords were evaluated using two metrics: keyword occurrences (OC) and keyword co-occurrences (CO). Keyword occurrences were derived from terms provided by the authors and extracted from titles, abstracts, and citation contexts. To ensure relevance, only keywords appearing at least three times were considered. Keywords were defined as co-occurring when two or more appeared together within the title, abstract, or citation context of an article. The primary metric for ranking keywords was OC, with CO used to resolve ties.

As shown in Table 4, "*Artificial Intelligence*" is the most frequent keyword, appearing 43 times with 195 co-occurrences, highlighting its central role in GenAI-driven risk management research in sustainable development. "*Sustainable development*" follows, with 20 occurrences and 84 co-occurrences, indicating its strong relevance. "Machine learning" ranks third with 16 occurrences and 94 co-occurrences. Other prominent keywords include "*Risk management*" (15 occurrences, 92 co-occurrences) and "*Project management*" (14 occurrences, 78 co-occurrences), both core to applying GenAI in managing risks and projects within sustainable development frameworks. Although "Artificial intelligence" dominates the keyword set, the comparatively lower visibility of governance- and sustainability-assurance terms suggests the literature is still partly technology-led rather than risk-and-sustainability-led. This may explain why sustainability benefits are often asserted rather than evidenced in implementation contexts: many studies emphasise capability and efficiency, while fewer specify assurance practices (e.g., validation, bias controls, accountability, and decision traceability) that determine whether GenAI outputs improve sustainable risk decisions. This supports the need for an integrated framework that explicitly links GenAI capability to risk-process improvements and, in turn, to triple-bottom-line sustainability outcomes under defined governance conditions.

Overall, these five keywords; "Artificial intelligence", "*Sustainable development*", "*Machine learning*", "*Risk management*" and "*Project management*", are central to the research domain, reflecting their importance and interconnectivity in the literature.

Table 4. *Most common author keyword occurrences*

Rank	keyword	OC	CO
1	Artificial intelligence	43	195
2	Sustainable development	20	84
3	Machine learning	16	94
4	Risk management	15	92
5	Project management	14	78
6	Construction industry	13	88
7	Risk assessment	12	72
8	Decision making	11	60
9	Sustainability	10	46
10	Deep learning	8	56
11	Natural language processing	8	53
12	Learning systems	7	55
13	Natural language processing systems	7	49
14	Learning algorithms	6	44
15	Risks management	6	43
16	Construction projects	6	34
17	Artificial intelligence (ai)	6	24
18	Accident prevention	5	38
19	Machine-learning	5	38
20	Life cycle	5	37

21	SLR	5	31
22	ChatGPT	5	26
23	Data mining	4	29
24	Risk analysis	4	28
25	Decision trees	4	27
26	Semantics	4	23
27	Robotics	4	20
28	SDGs	4	17
29	Fuzzy logic	4	11
30	Architectural design	3	28

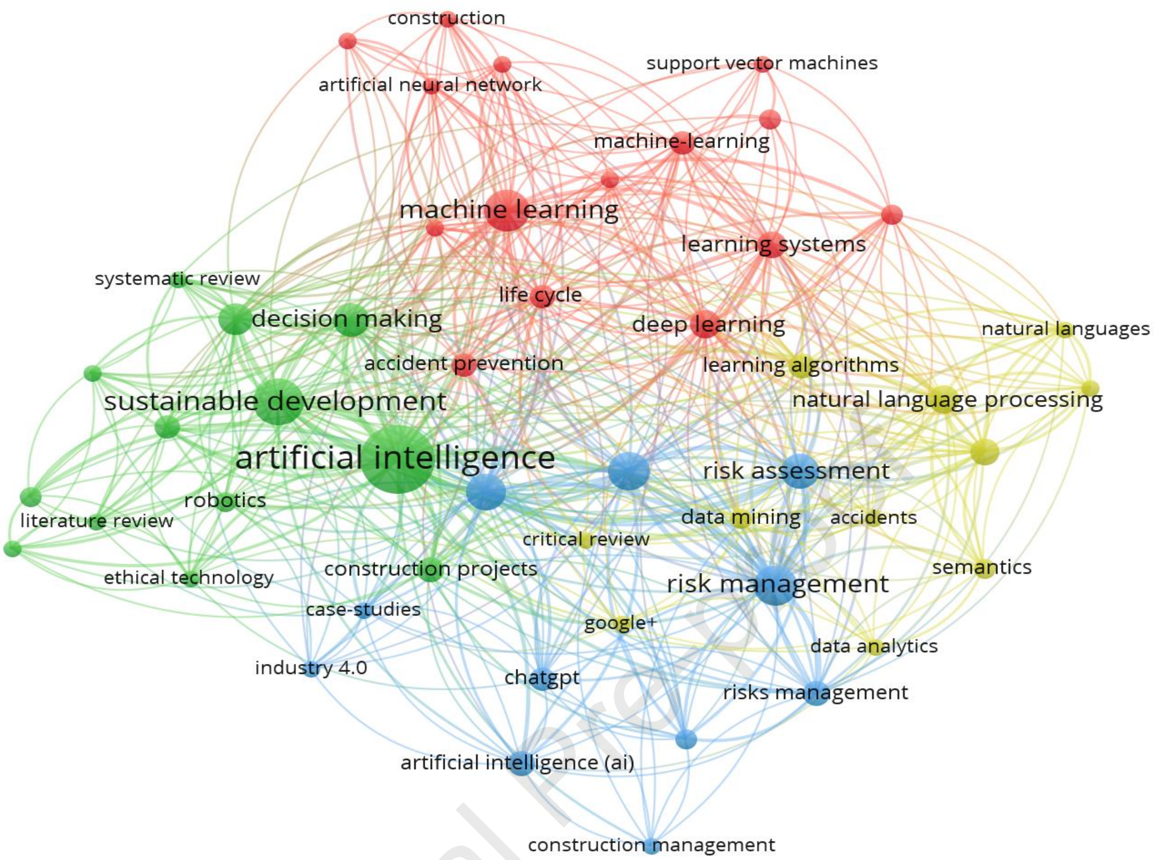
Oc = Keywords occurrence; Co = keywords Co-occurrence

To further explore these relationships, VOSviewer software was employed to visualise the network and connections among keywords (see Figure 3). In this graphical representation nodes indicate the frequency of keyword occurrences, with larger nodes representing higher frequencies. Additionally, Links between nodes illustrate relationships between keywords, where thicker lines signify a higher frequency of co-occurring keywords. While Shorter lines denote closer proximity and relatedness between keywords. Also, Different colours are used to distinguish groups of co-occurring keywords. therefore, this visualisation aids in understanding the complexity and depth of research surrounding GenAI-driven project risk management in sustainable development, highlighting the interconnected nature of the key research. Finally, Figure 3 shows three main clusters in the literature, a technical and analytics stream centred on AI methods and automated risk functions, a management stream focused on risk assessment and decision making in project contexts, and a domain stream reflecting applications in construction delivery.

While, table 4 supports this structure, with the most frequent keywords showing the strongest co-occurrence links, indicating that these themes are repeatedly discussed together rather than in isolation. Notably, keywords such as “risk management”, “risk assessment”, and “decision making” act as bridge terms connecting the technical cluster (AI/ML/NLP methods) with project delivery and construction applications, highlighting that GenAI is primarily framed as decision-support for risk processes.

Overall, the clustering suggests the field is currently shaped more via capability and implementation themes than governance or social sustainability, since terms linked to accountability, assurance, and social sustainability are less prominent, indicating a gap in research that integrates these requirements into GenAI-driven risk management.

Figure 3. keyword occurrence and co-occurrence of author keywords



3.3 Most contributing countries

The Total Papers (*TP*) metric represents the number of articles published in a research field by a given country. For articles authored by researchers from multiple countries, each contributing country receives credit, rather than attributing the paper to a single nation. Table 5 summarises the contributions of various countries between 2014 and 2024, detailing both the number of published papers and their citations.

When two or more countries have the same TP, rankings are determined by Total Citations (*TC*), which reflects the cumulative number of citations received by a country's publications. The United Kingdom leads with 12 published papers and 817 citations, demonstrating its active role in this research area. The United States, despite having slightly fewer papers (11), ranks second due to its exceptionally high citation count of 2,493, indicating strong research impact and influence. China ranks third with 8 papers and 408 citations, reflecting steady research output. Australia follows with 6 papers and 652 citations, showing a high citation impact per paper. Malaysia and India each contributed 5 papers, but Malaysia ranks fifth due to a higher total citation count (184 versus India's 154).

This analysis highlights that while some countries, such as the United States and Singapore, produce fewer papers, their research is highly cited and influential. In contrast, countries like the United Kingdom demonstrate high publication activity, indicating substantial engagement in the field. Therefore, the concentration of publications and citations within a small number of countries indicates that the evidence base is being shaped largely by higher-income contexts with stronger research capacity and digital infrastructure, with comparatively limited representation from developing countries. Moreover, high citation counts in countries with fewer publications, such as the United States and Singapore, may indicate that a small number of highly visible papers are being published in prominent outlets or addressing widely cited cross-cutting themes, leading to higher citation intensity per paper rather than greater publication volume.

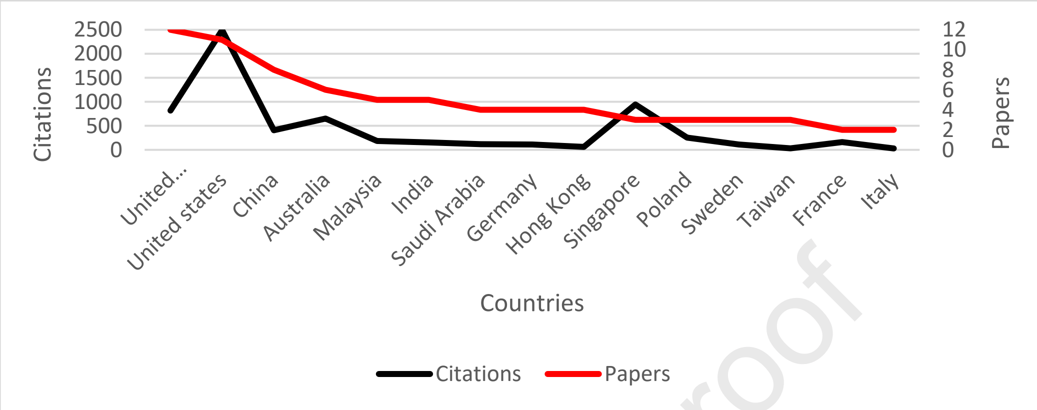
Furthermore, the geographic concentration of publications suggests that evidence and implementation assumptions may reflect specific regulatory environments, digital maturity levels, and data availability. For sustainable development projects, this matters because sustainability priorities and risk governance expectations vary by jurisdiction; therefore, the transferability of findings should be treated cautiously. This further motivates the framework's emphasis on governance, organisational readiness, and data quality as contextual conditions rather than universal guarantees of benefit.

Table 5. Countries contribution between 2014-2024

Rank	Country	*TP*	*TC*
1	United Kingdom	12	817
2	United states	11	2493
3	China	8	408
4	Australia	6	652
5	Malaysia	5	184
6	India	5	154
7	Saudi Arabia	4	117
8	Germany	4	112
9	Hong Kong	4	61
10	Singapore	3	943
11	Poland	3	256
12	Sweden	3	111
13	Taiwan	3	30
14	France	2	162
15	Italy	2	29

Figure 4 presents the leading countries in the research field, combining total paper numbers (*TP*) and total citations (*TC*) in a single graph. This approach enables comparison of both research productivity and impact, illustrating which countries publish extensively and which generate highly cited, influential work. By displaying both metrics together, the figure provides a clear overview of each country's research output and influence in the field.

Figure 4. Total paper numbers and citations per country



3.4 Drivers of GenAI-driven project risk management

the observed publication growth and dominant keywords indicate rising interest in GenAI adoption; the drivers below therefore explain the main "push factors" behind this trend in sustainable project risk management. Additionally, the rapid evolution of Generative AI (GenAI) and machine learning (ML) technologies is playing a pivotal role in advancing risk management practices, particularly within the context of sustainable development. Research by Greif et al. (2024) and Gupta et al. (2023) demonstrates that cutting-edge GenAI algorithms enhance the accuracy and efficiency of project risk management. As these technologies continue to evolve, they become increasingly capable of addressing complex risk scenarios, which is critical for projects aiming to achieve sustainability goals. For example, advanced GenAI can better predict risks and support risk mitigation by assisting project teams in identifying, analysing, and responding to emerging risk conditions related to environmental impacts, supporting the implementation of more sustainable practices and projects. The drivers below distinguish between general digital and AI adoption pressures, such as regulation, productivity, and competitiveness, and GenAI-specific enablers that are distinctive to generative models and directly reshape risk-management tasks.

The exponential growth of digital data, including sensor data and historical project data, further amplifies the potential of GenAI in risk management. In line with Li et al. (2022) and

Liao et al. (2022), abundant data allows GenAI systems to provide more accurate and actionable insights on sustainability-related risks. Access to large datasets enables GenAI to improve predictions of environmental hazards and resource utilisation, thereby enhancing decision-making and supporting sustainability-oriented risk management in sustainable development projects. Unlike conventional AI, GenAI can synthesise unstructured project information such as reports, logs, and contracts, rapidly generate risk narratives and proposed controls, and support scenario-based what-if exploration, enabling earlier identification of emerging risks and faster decision support.

The increasing emphasis on sustainability and green building practices also drives the adoption of advanced GenAI technologies. Research by Kazeem et al. (2023) and McMillan and Varga (2022) indicate that growing demand for sustainable solutions motivates organisations to leverage GenAI tools for effective assessment and management of environmental risks. By embedding sustainability criteria into these systems, organisations can optimise resource use, reduce waste, and minimise environmental impact, contributing directly to broader sustainability objectives. Advanced GenAI technologies thus provide organisations with a competitive advantage, particularly in the domain of sustainable development project risk management.

State-of-the-art GenAI also supports risk-conscious project management, enabling organisations to design more efficient and durable solutions (Jallow et al., 2023; Pillai and Matus, 2020). This capability strengthens organisations' strategic positions by improving risk management processes, fostering sustainability, and enhancing competitive differentiation.

Regulatory pressures related to environmental sustainability and project risk management represent another key driver for GenAI adoption. Al-Saffar et al. (2024) and Adewale et al. (2024) note that increasingly stringent regulations encourage organisations to integrate advanced tools like GenAI to ensure compliance. By accurately identifying and mitigating risks, GenAI enables organisations to navigate complex regulatory landscapes while meeting sustainability standards. This not only facilitates compliance but also reinforces the objectives of sustainable development, promoting responsible and environmentally friendly practices in projects. However, these drivers are context-dependent and can operate in tension. Regulatory pressure may encourage adoption to strengthen auditability and compliance, yet it can also discourage experimentation when model uncertainty, accountability concerns, or data-governance risks increase exposure to non-compliance.

3.5 Challenges and risks

In contrast to the technology-forward emphasis seen in the bibliometric results, the challenges below highlight the governance, data, and organisational constraints that condition whether GenAI adoption produces reliable sustainability-related risk decisions. Despite the widespread recognition of GenAI's potential to advance sustainable development, there remains a notable lack of in-depth analysis regarding its specific applications, impacts, and associated challenges (Regona et al., 2024). Many projects continue to face complex issues, including cost and time overruns, health and safety concerns, low productivity, and labour shortages. While digitalisation has the potential to mitigate these challenges, effectively leveraging it in project contexts remains a significant hurdle (Abioye et al., 2021).

To minimise overlap, this study differentiates challenge categories by primary locus. Legal concerns relate to compliance obligations, including data protection, liability, contracting, and regulatory requirements. Ethical concerns relate to fairness, transparency, accountability, and trust in automated outputs. Resource concerns relate to organisational capability, including skills, training, budget, and change capacity. Technical concerns relate to model and data performance and reliability, including data quality, hallucination risk, robustness, and cybersecurity. Integration concerns relate to embedding GenAI within existing processes, tools, governance workflows, and decision rights. Where an issue spans categories, it is discussed under the category that best reflects the dominant mechanism, such as compliance, trust, or system design.

3.5.1 Legal- related

The use of GenAI driven risk management in sustainable development creates several legal issues related to regulatory compliance, accountability, and data governance. According to Liengpunsakul (2021), lacking clear regulations regarding GenAI hinders broader use and innovation. The lack of standardised GenAI applications in projectized industry sectors further complicates compliance, as there is no consistent application of regulations related to the management and integration of data (Pan and Zhang, 2021). Additionally, accountability issues are one of the many concerns, where decisions made through GenAI can sometimes be very unclear since many people have involvement in developing GenAI, which makes accountability hard to point out (Holzmann and Lechiara, 2022). It is particularly a big problem in areas critical in terms of safety since even a small mistake might be catastrophic. Other serious concerns are sensitive data management, such as personal or private company information, and how such sensitive data needs to have stringent data management to ensure privacy against data breaches (Pillai and Matus, 2020)

3.5.2 Ethical and organizational-related

The use of GenAI in sustainable projects introduces several significant ethical and practical challenges. One key concern is algorithmic bias, which may arise from flawed training data or imperfections in the algorithms themselves. Such biases can have serious consequences in critical areas such as human resources, safety, and regulatory compliance (Pan and Zhang, 2021). Deep learning models often function as “black boxes,” making their outputs difficult to interpret and raising transparency concerns (Najafabadi et al., 2015).

Data privacy and security are increasingly important in the context of digitalised projects. Sensitive information, including proprietary designs, financial data, and personal details, requires robust protection through encryption, access controls, and regular security audits (Adewale et al., 2024). Ethical concerns also extend to how GenAI systems manage this data, with risks of privacy violations and potential misuse in applications such as facial recognition (Yigitcanlar et al., 2020; Liengpunsakul, 2021).

Cultural resistance among project professionals further complicates AI adoption. Many may hesitate to embrace GenAI due to unfamiliarity or perceived lack of transparency in AI-based decision-making (Kulkarni et al., 2017; Pan and Zhang, 2021). Additionally, insufficient engagement with key stakeholders during implementation can lead to mismatches between GenAI capabilities and stakeholder expectations, reflecting a limited understanding of AI’s potential and constraints (Yaseen et al., 2020).

Finally, the automation of jobs through GenAI raises concerns about employment security across sectors (Truby, 2020). Collectively, these challenges underscore the need for clear ethical guidelines, well-defined regulatory frameworks, and effective stakeholder engagement to ensure the responsible and sustainable deployment of GenAI in project environments.

3.5.3 Resources-related

The deployment of GenAI tools in sustainable development faces several resource-related challenges, primarily concerning scalability, cost, and specialised skills. Scalability is a key issue, as artificial neural network (ANN) models developed for one project may not easily transfer to others due to differences in data, conditions, or project requirements (Lishner and Shtub, 2022). This limitation constrains the broader adoption of GenAI across projectised sectors (Choi et al., 2021; Kulkarni et al., 2017; Afzal et al., 2021).

High initial costs also pose a significant barrier. Implementing GenAI solutions requires substantial investments in hardware, software, training, and infrastructure, which may be unaffordable for many organisations. These costs extend beyond system customisation and integration to include continuous updates, necessitating careful assessment of potential return on investment (Al-Saffar et al., 2024; Behrooz et al., 2023; Hannan et al., 2021).

Furthermore, the successful adoption of GenAI requires competent human resources with expertise in machine learning, programming, and data analysis (Abioye et al., 2021). The shortage of trained personnel remains a major obstacle, highlighting the need for investment in workforce development and training programs (Adewale et al., 2024). Reliable infrastructure is also critical, as deep learning models demand substantial computational power and data storage, resources that smaller organisations may lack (Parveen, 2018; Najafabadi et al., 2015).

Addressing these challenges, scalability, high costs, skills gaps, and infrastructure requirements, is essential to ensure the effective deployment and impactful utilisation of GenAI technologies in sustainable development projects.

3.5.4 Technical-related

GenAI-driven project risk management faces numerous technical challenges arising from the complexity of GenAI models, data quality issues, and the dynamic nature of projects. One key challenge is the technical complexity involved in designing artificial neural networks (ANNs), including determining the configuration of input, hidden, and output nodes (Lishner and Shtub, 2022). This process is often problem-specific and lacks standardization, making adoption difficult for many organisations (Kulkarni et al., 2017). Moreover, deep learning models require advanced knowledge of machine learning algorithms, data preprocessing, and model training, which can be overwhelming for teams without a strong technical background (Choi et al., 2021).

The unpredictable nature of project environments further complicates the adaptation of ANN models (Kulkarni et al., 2017; Manzoor et al., 2021). Data quality and availability are additional barriers: poor-quality, incomplete, or inconsistently formatted data significantly reduce model performance, while limited access to comprehensive datasets, due to confidentiality or proprietary restrictions, hinders effective training (Choi et al., 2021; Behrooz et al., 2023; Al-Saffar et al., 2024). Integrating diverse data sources, such as sensor data and Building Information Modelling (BIM), into a cohesive format for GenAI applications presents further technical challenges (Regona et al., 2022).

Other issues include overfitting, where models fail to generalise beyond training data. Mitigating this requires specialized techniques such as early stopping and regularization (Kulkarni et al., 2017). GenAI systems also demand ongoing maintenance, including continuous updates and retraining to adapt to new data and changing project conditions, which requires sustained resources and technical expertise (Choi et al., 2021).

The technical complexity of GenAI systems in project risk assessment remains a fundamental barrier to wider adoption. Implementing and maintaining these systems often requires specialised knowledge of algorithms and control methods, such as Levenberg-Marquardt or Bayesian regularization, which may not exist within the organisation (Hannan et al., 2021; Al-Saffar et al., 2024). Access to large, labelled datasets for training deep learning models is another critical challenge, as acquiring such data can be costly and time-consuming. Some project environments simply lack the extensive datasets required for advanced GenAI models like GPT (Najafabadi et al., 2015; Saka et al., 2023). Consequently, organisations must invest in data collection and labelling processes to enhance the accuracy and reliability of GenAI systems.

Given these technical complexities and data limitations, the full potential of GenAI may not yet be achievable in certain projectised industry sectors.

3.5.5 Integration-related

The primary challenges of integrating GenAI-driven risk management into the workflows of sustainable projects arise from the incompatibility of existing systems with advanced GenAI technologies. Many firms involved in project delivery still rely on outdated systems, making integration technically complex and costly (Choi et al., 2021). This issue is particularly pronounced in complex EPC projects, where the seamless integration of multiple data sources and software platforms is critical for smooth operations (Kulkarni et al., 2017; Pan and Zhang, 2021). Furthermore, highly sophisticated GenAI models, such as GPT, require specialised expertise that is currently underdeveloped within the industry, further complicating effective integration (Saka et al., 2023).

However, challenge prioritisation is context-dependent rather than uniform. In regulated environments, legal and ethical constraints often act as gatekeepers because unresolved liability, privacy, and accountability issues can prevent deployment regardless of technical capability. By contrast, in lower digital-maturity settings, technical and data readiness and resource capability, including skills, infrastructure, and investment, tend to be the dominant barriers, with governance arrangements often developing later. Differences are also evident between developed and developing economies: where capacity is limited, studies more frequently emphasise skills, infrastructure, and data availability, whereas in higher-scrutiny contexts, governance and accountability requirements are more prominent.

3.6 Impact of integrating GenAI driven project risk management

In this review, environmental, social, and economic impacts are interpreted through a risk-management mechanism. GenAI contributes to sustainability primarily when it strengthens core risk activities, including risk identification, assessment, response planning, and monitoring and control. Accordingly, sustainability outcomes are not attributed to GenAI in general, but to GenAI-enabled improvements in how sustainability-related risks are detected earlier, assessed more consistently, and managed more proactively across the project lifecycle. Taken together, these impacts should be interpreted alongside the drivers and challenges above, because the sustainability outcomes reported in the literature are typically conditional on data quality, oversight, and integration into existing risk processes. Additionally, these impacts are discussed specifically in the context of sustainable development projects, where risk decisions are directly tied to SDG-aligned outcomes and defined sustainability performance requirements.

3.6.1 Environment impact

GenAI plays a pivotal role in managing environmental impacts throughout a project's lifecycle, supporting sustainability objectives. Wu and Shang (2020) and Zhou et al. (2024) demonstrate that GenAI can monitor environmental factors from planning through execution, ensuring efficient resource use and minimizing waste. This lifecycle management reduces the ecological footprint of project activities and enhances environmental sustainability.

GenAI also enables early identification of environmental risks, allowing mitigation strategies to be implemented proactively to reduce harmful impacts such as pollution and habitat disruption (Nyqvist et al., 2024; Fridgeirsson et al., 2023). According to Waqar et al. (2023), GenAI ensures projects are designed with sustainability in mind, promoting efficient resource use, minimizing emissions, and supporting long-term environmental goals.

The technology further enhances environmental planning through simulations of various risk scenarios, enabling the development of proactive and eco-friendly project designs (Turek et al., 2023; Giraud et al., 2023). GenAI facilitates comprehensive scenario planning, allowing firms to adapt operations to be more resilient and sustainable (Boughaba and Bouabaz, 2020). Li et al. (2022) and Greif et al. (2024) highlight that scenario planning helps avoid environmentally sensitive areas and suggests alternative methods to minimize environmental damage, promoting effective environmental stewardship.

Real-time monitoring of environmental factors, such as emissions and waste, is another key capability of GenAI. Studies by An et al. (2021) and Liao et al. (2022) show that such monitoring helps firms stay within environmental limits and reduce carbon footprints. Zhang et al. (2020) and Yigitcanlar et al. (2020) illustrate that real-time insights enable immediate corrective actions, ensuring compliance with sustainability regulations. Zhou et al. (2024) and Wankhede et al. (2024) further highlight GenAI's role in helping companies meet environmental standards, avoid regulatory fines, and deliver projects in a more sustainable manner.

3.6.2 Social impact

GenAI plays a critical role in enhancing worker safety and supporting social sustainability in projects. Choi et al. (2021) and Regona et al. (2022) illustrate how GenAI predicts potential hazards, reducing accidents and fostering safer work environments. This predictive capability aligns with social sustainability by prioritising human well-being. Yaseen et al. (2020) highlight the use of GenAI-driven systems for continuous monitoring of safety protocols, ensuring that workers operate under safe conditions. Similarly, Akinosho et al. (2020) and Waqar et al. (2023) emphasise AI's ability to predict and mitigate health and safety risks, further supporting the social objectives of sustainable development.

GenAI also enhances communication and collaboration among project stakeholders, contributing to socially sustainable project environments. Kulkarni et al. (2017) and Boinot et al. (2023) show that GenAI facilitates collaboration by providing shared insights, while Erfani and Cui (2022) highlight how AI platforms increase transparency by allowing stakeholders to access real-time data. Turek et al. (2023) further emphasise that GenAI bridges communication gaps within project teams, ensuring that all stakeholders can participate in decision-making, which aligns with the principles of inclusivity and social sustainability.

Beyond immediate safety, GenAI contributes to lifecycle management and long-term infrastructure resilience, supporting the creation of socially sustainable projects. Parveen (2018) and Olanrewaju (2022) demonstrate that AI's ability to assess risks throughout a project's lifecycle ensures infrastructure provides long-term benefits to communities. Smith and Wong (2022) argue that incorporating community impacts into AI-driven risk assessments results in infrastructure that serves communities effectively while minimising disruption. Regona et al. (2024) and Baduge et al. (2022) further show that GenAI promotes lifecycle thinking, ensuring that maintenance and operational phases are socially sustainable and reducing the need for frequent repairs or replacements.

3.6.3 Economic impact

GenAI-driven project risk management significantly enhances economic sustainability by improving cost predictability, scenario planning, reporting, and real-time risk monitoring. Costantino (2015) and Pan and Zhang (2021) highlight that AI-based tools enhance budget accuracy and financial stability by identifying risks early and enabling precise forecasting. This capability helps avoid unexpected financial burdens and allows for more effective resource management. Adewale et al. (2024) and Singh et al. (2023) further illustrate that GenAI tools can assess the financial impacts of potential risks before they materialize, facilitating better resource allocation and cost reduction.

In terms of scenario planning, Chou et al. (2024) and Boughaba and Bouabaz (2020) emphasise AI's ability to simulate risk scenarios, helping anticipate disruptions and mitigate financial losses, thereby supporting long-term economic growth. Pillai and Matus (2020) and Giraud et al. (2023) highlight AI's contribution to reducing costly delays through effective contingency planning.

Enhanced reporting through AI improves transparency and accountability, aligning financial management with SDGs (Abioye et al., 2021; Saka et al., 2023). Liang et al. (2024) and McMillan and Varga (2022) show that real-time monitoring reduces inefficiencies and financial disruptions, ensuring timely project completion and optimal resource utilization. Muller et al.

(2024) and Kar et al. (2022) further emphasize AI's role in minimizing financial waste and project delays.

Accordingly, the framework integrates bibliometric patterns with the identified drivers, challenges, and impacts to make the GenAI-to-risk-process-to-sustainability mechanism explicit.

3.7 Framework for GenAI-driven risk management integration

The purpose of this framework is to provide a comprehensive model for GenAI-driven risk management within sustainable development projects, addressing the complexity and fragmented understanding of the relationships between GenAI and project risk management. As illustrated in Figure 5, the framework bridges a significant research gap by integrating insights from existing literature. Comparable frameworks include Eacersall et al. (2024), who developed a model to navigate ethical challenges in generative AI, Dacre et al. (2024), who proposed a framework to explore barriers to Industry 5.0 adoption in supply chain management, and Anica et al. (2021), who highlighted the benefits and challenges of GenAI integration in the retail sector. Building on these methodologies, our framework specifically targets sustainable development projects.

The framework in Figure 5 is directly derived from the results reported in Sections 3.4–3.6. Its core structure is anchored in the 23 challenges synthesised from the included studies as shown in Table 6, grouped into five categories to reduce fragmentation and highlight interdependencies. The adoption drivers component reflects the drivers identified in Section 3.4, explaining why organisations pursue GenAI-driven risk management in sustainable projects. The sustainability impacts component reflects the environmental, social, and economic impacts synthesised in Section 3.6, interpreted as outcomes of GenAI-enabled improvements in the risk-management process. Appendix A provides a consolidated mapping of included studies to drivers, impacts, and challenges, demonstrating how the evidence base informed the framework design.

These categories form the core components, collectively addressing: (i) defining the concepts and applications of GenAI, (ii) exploring the drivers of GenAI-driven risk management adoption in sustainable development, (iii) assessing the sustainability impacts of adoption, and (iv) identifying integration challenges. By structuring these elements consistently, the framework provides a clear pathway for understanding how GenAI-driven risk management can support sustainable development objectives while highlighting the associated challenges.

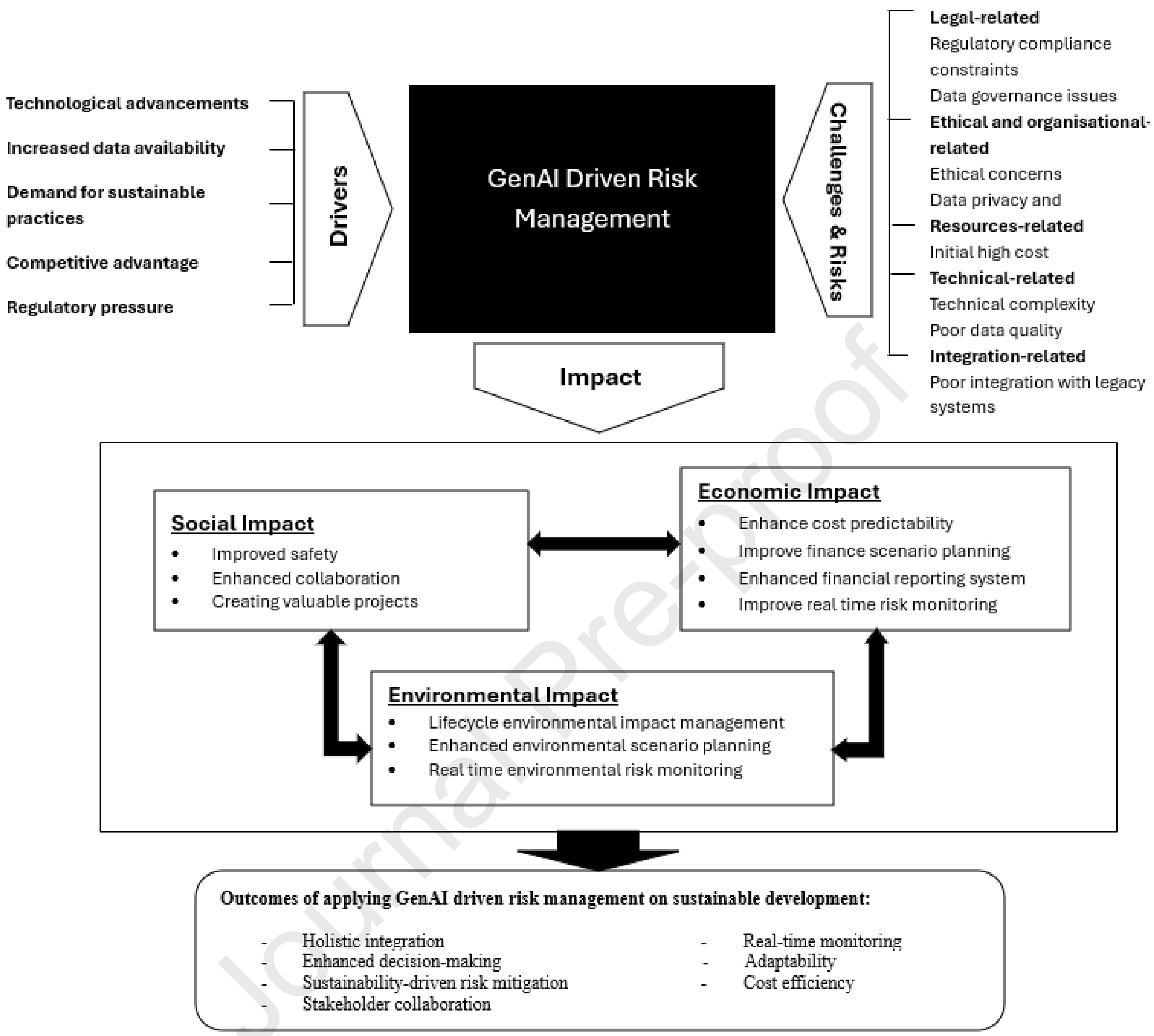
Table 6. Challenges and risks of integrating GenAI into project risk management

Category	Challenge and risks	Reference
Legal-related	Regulatory compliance constraints	(Holzmann and Lechiara, 2022), (Regona et al., 2022), (Yigitcanlar et al., 2022), (Waqar et al., 2023), (Parveen, 2018), (Liang et al., 2024), (Wijayasekera et al., 2022), (Gupta et al., 2023)
	Accountability gaps	(Regona et al., 2022), (Adekunle et al., 2022), (Wijayasekera et al., 2022)
	Data governance issues	(Pillai and Matus, 2020), (Regona et al., 2022), (Parveen, 2018), (Adekunle et al., 2022), (Lee and Shin, 2020), (Liang et al., 2024), (McMillan and Varga, 2022), (Zhao, 2024), (Gupta et al., 2023)
Ethical and organizational-related	Ethical concerns	(Regona et al., 2022), (Pillai and Matus, 2020), (Holzmann and Lechiara, 2022), (Yigitcanlar et al., 2022), (Waqar et al., 2023), (Tang and Golparvar, 2021), (Lee and Shin, 2020), (Liang et al., 2024), (An et al., 2021), (Wijayasekera et al., 2022), (Gupta et al., 2023)
	Data privacy and security vulnerabilities	(Regona et al., 2022), (Holzmann and Lechiara, 2022), (Yigitcanlar et al., 2022), (Tang and Golparvar, 2021), (Lee and Shin, 2020), (Liang et al., 2024), (Wijayasekera et al., 2022), (Zhao, 2024), (Gupta et al., 2023)
	Cultural resistance	(Holzmann and Lechiara, 2022), (Regona et al., 2022), (Eber, 2020), (Yigitcanlar et al., 2022), (Tang and Golparvar, 2021), (An et al., 2021), (Wijayasekera et al., 2022)
	Lack of stakeholder engagement	(Holzmann and Lechiara, 2022), (Tang and Golparvar, 2021)
	Lack of awareness	(Pillai and Matus, 2020), (Regona et al., 2022), (Holzmann and Lechiara, 2022), (Yigitcanlar et al., 2022), (Waqar et al., 2023), (Tang and Golparvar, 2021), (An et al., 2021), (Wijayasekera et al., 2022)
	Trust deficiency	(Pillai and Matus, 2020), (Regona et al., 2022), (Holzmann and Lechiara, 2022), (Yigitcanlar et al., 2022), (Liang et al., 2024), (An et al., 2021), (Wijayasekera et al., 2022), (Gupta et al., 2023), (Boinot et al., 2023)
Resources-related	Scalability limitations	(Anysz et al., 2021), (Regona et al., 2022), (Kulkarni et al., 2017), (Holzmann and Lechiara, 2022), (Yigitcanlar et al., 2022), (Adekunle et al., 2022)

	Initial high Cost	(Pillai and Matus, 2020), (Kulkarni et al., 2017), (Yigitcanlar et al., 2022), (Regona et al., 2022), (Parveen, 2018), (Adekunle et al., 2022), (Tang and Golparvar, 2021), (Wijayasekera et al., 2022), (Adewale et al., 2024), (Al-Saffar et al., 2024)
	Skills Gap	(Holzmann and Lechiara, 2022), (Yigitcanlar et al., 2022), (Parveen, 2018), (Pillai and Matus, 2020), (Regona et al., 2022), (Yigitcanlar et al., 2022), (Waqar et al., 2023), (Tang and Golparvar, 2021), (Wijayasekera et al., 2022), (Adewale et al., 2024), (Al-Saffar et al., 2024)
	Infrastructure reliability concerns	(Parveen, 2018), (Regona et al., 2022), (Adekunle et al., 2022), (Tang and Golparvar, 2021), (Louis, and Dunston, 2018), (Wijayasekera et al., 2022)
Technical-related	Technical Complexity	(Holzmann and Lechiara, 2022), (Yigitcanlar et al., 2022), (Parveen, 2018), (Tang and Golparvar, 2021)
	Unpredictable construction environment	(Anysz et al., 2021), (Regona et al., 2022), (Kulkarni et al., 2017), (Holzmann and Lechiara, 2022), (Yigitcanlar et al., 2022), (Parveen, 2018), (Adekunle et al., 2022), (McMillan and Varga, 2022)
	Poor data quality	(Anysz et al., 2021), (Regona et al., 2022), (Kulkarni et al., 2017), (Holzmann and Lechiara, 2022), (Regona et al., 2022), (Yigitcanlar et al., 2022), (Adekunle et al., 2022), (Lee and Shin, 2020), (Zou et al., 2017), (McMillan and Varga, 2022), (Wijayasekera et al., 2022), (Zhao, 2024), (Adewale et al., 2024), (Boinot et al., 2023)
	Data unavailability	(Anysz et al., 2021), (Regona et al., 2022), (Kulkarni et al., 2017), (Holzmann and Lechiara, 2022), (Pillai and Matus, 2020), (Regona et al., 2022), (Eber, 2020), (Yigitcanlar et al., 2022), (Parveen, 2018), (Adekunle et al., 2022), (Tang and Golparvar, 2021), (Lee and Shin, 2020), (Lee and Yu, 2023), (Zou et al., 2017), (An et al., 2021), (McMillan and Varga, 2022), (Zhao, 2024)
	Complex data (construction feature)	(Anysz et al., 2021), (Regona et al., 2022), (Kulkarni et al., 2017), (Holzmann and Lechiara, 2022), (Regona et al., 2022), (Yigitcanlar et al., 2022), (Parveen, 2018), (Adekunle et al., 2022), (Aladag, 2023), (Lee and Shin, 2020), (An et al., 2021), (McMillan and Varga, 2022), (Al-Saffar et al., 2024), (Boinot et al., 2023)

	Data Overfitting (failure to generalise)	(Anysz et al., 2021), (Regona et al., 2022), (Kulkarni et al., 2017), (Holzmann and Lechiara, 2022), (Pillai and Matus, 2020), (Eber, 2020), (Yigitcanlar et al., 2022), (Adekunle et al., 2022)
	Data uniformity (lack of diversity)	(Anysz et al., 2021), (Regona et al., 2022), (Kulkarni et al., 2017), (Pillai and Matus, 2020), (Regona et al., 2022), (Eber, 2020), (Yigitcanlar et al., 2022), (Parveen, 2018), (Adekunle et al., 2022), (Aladag, 2023), (Liang et al., 2024), (McMillan and Varga, 2022)
	Biased data	(Regona et al., 2022), (Holzmann and Lechiara, 2022), (Pillai and Matus, 2020), (Eber, 2020), (Parveen, 2018), (Adekunle et al., 2022), (Afzal et al., 2021), (Lee and Shin, 2020), (Liang et al., 2024), (An et al., 2021), (Wijayasekera et al., 2022), (Al-Saffar et al., 2024)
	Incorrect decision	(Holzmann and Lechiara, 2022), (Chenya et al., 2022), (Al-Mhdawi, et al. 2023), (Fridgeirsson et al., 2023), (Hashfi and Raharjo, 2023), (Barcaui and Monat, 2023), (An et al., 2021), (Al-Saffar et al., 2024), (Behrooz et al., 2023)
Integration-related	Poor integration with legacy systems	(Pillai and Matus, 2020), (Yigitcanlar et al., 2022), (Parveen, 2018), (Regona et al., 2022), (Adekunle et al., 2022), (Tang and Golparvar, 2021), (An et al., 2021), (Al-Saffar et al., 2024), (Boinot et al., 2023)

Figure 5. *GenAI Driven risk management framework*



For project managers, the findings support using GenAI as decision support within existing risk governance, rather than as a replacement for professional judgement. Priority actions include strengthening data readiness and secure access controls for risk-relevant documents such as reports, logs, and contracts, establishing clear human-in-the-loop review for high-stakes risk decisions, and implementing validation and monitoring routines to manage unreliable outputs. For policymakers and clients, the framework informs procurement and assurance requirements that set expectations for accountability, data governance, and transparency, and that require minimum validation evidence for GenAI tools used in sustainability-critical project decisions.

4. Conclusion

This research presents a comprehensive approach to applying GenAI for risk management in sustainable development projects, providing a structured pathway for stakeholders to implement AI-driven solutions aligned with the SDGs. While the potential benefits of GenAI span environmental, social, and economic dimensions, adoption challenges persist. Legal, technical, ethical, and integration-related barriers, together with biases in AI systems and data privacy concerns, can delay implementation and affect efficiency, trust, and financial stability. Resource-related constraints, such as high initial costs, scalability issues, and shortages of skilled professionals, further influence the economic viability of GenAI applications. Addressing these challenges is essential for fostering stakeholder confidence and ensuring the responsible integration of GenAI into project risk management, thereby supporting outcomes such as energy efficiency, waste reduction, and broader SDG-related objectives.

However, it is important to emphasise that this study is explicitly grounded in construction-sector projects, and the analysis, evidence base, and framework development are derived from literature focused on construction project contexts. Accordingly, the proposed framework and its findings are primarily applicable to sustainable development projects delivered in construction environments, where project organisation, risk profiles, and governance arrangements exhibit distinct characteristics.

Addressing Research Question 1, the reviewed literature indicates that GenAI-driven risk management can influence sustainable development projects through strengthened risk identification, assessment, decision support, and monitoring in ways that support environmental, social, and economic outcomes, provided that governance safeguards and data quality are adequate. Addressing Research Question 2, the synthesis identifies the main drivers motivating adoption and consolidates the key challenge categories, namely legal, ethical and organisational, resource, technical, and integration-related factors, that determine whether these impacts can be realised in practice.

Despite these limitations, GenAI offers transformative opportunities through enhanced risk identification, decision-making, and response strategies. Improvements in resource management, safety performance, cost predictability, and regulatory compliance contribute to stronger sustainability outcomes in project practices. Nevertheless, the current literature lacks in-depth analysis of GenAI's specific implications for risk management in sustainable development projects, particularly in relation to long-term governance, assurance, and implementation outcomes. Further research is therefore required to refine integration methodologies and develop solutions that mitigate the challenges identified in this study.

From a theoretical perspective, this study develops a comprehensive framework linking the drivers, challenges, and benefits of GenAI-driven project risk management, offering insights into its role in sustainable development. The framework provides a structured perspective on how GenAI enhances risk identification, decision-making, and response strategies while addressing the inherent complexity of project sustainability. In line with Figure 5, the framework advances the discourse by operationalising environmental, social, and economic considerations as explicit risk criteria and impact pathways within the GenAI-enabled risk management process, demonstrating how improvements in risk identification, assessment, and response can translate into sustainability outcomes in sustainable development projects. The synthesis of fragmented insights into a unified model enables the study to capture the multidimensional impact of GenAI on project risk management.

From a practical standpoint, the study provides a roadmap for stakeholders to implement GenAI-driven risk management solutions in alignment with the SDGs. The framework addresses key barriers, including high initial costs, skills shortages, scalability limitations, and legal or technical challenges that often impede the adoption of advanced technologies. The identification of these challenges and the proposal of strategic responses enhance the feasibility of integrating GenAI into project risk management practice. The study also highlights tangible benefits, such as improved resource efficiency, safety performance, cost predictability, regulatory compliance, and reduced environmental impact, demonstrating the economic and operational value of GenAI adoption.

4.1 Limitations

This study has several limitations that should be acknowledged when interpreting its findings. First, the six categories of challenges and risks, legal, ethical, organisational, resource, technical, and integration-related, were identified through a systematic literature review. While regulatory constraints across project-based industries beyond construction could be explored further through case studies or expert interviews, differences across other industries extend beyond regulatory frameworks alone. Variations in project structural features, including lifecycle configurations and supply-chain arrangements, project characteristics, such as safety criticality and data availability, and contextual conditions, including digital maturity, governance structures, and institutional operating environments, may substantially shape how GenAI-driven risk management can be implemented and governed. Second, the review is explicitly bounded to the construction sector. While construction represents one of the most projectised industries and offers a relevant testbed for sustainable development initiatives, this sectoral focus limits the transferability of findings to other project-based domains such as healthcare, energy, or IT infrastructure. Differences in regulatory regimes, lifecycle structures, safety criticality, and digital maturity may influence how GenAI-driven risk management is adopted and governed across industries. Finally, the study does not empirically test the proposed framework. Although the framework consolidates drivers, challenges, and sustainability impacts, its effectiveness in improving real-world risk mitigation, governance quality, or sustainability performance has yet to be longitudinally examined.

4.2 Future research directions

Building on these limitations several avenues for future research are proposed. First, empirical validation of the proposed framework is essential through quantitative approaches such as structural equation modelling to test causal relationships between GenAI adoption drivers governance conditions risk management improvements and sustainability outcomes alongside qualitative methods including Delphi studies and expert interviews to refine the framework constructs and contextual relevance. Second, future studies should extend the framework beyond the construction sector through cross industry comparative research to examine whether the identified drivers risks and sustainability pathways remain consistent across different project environments or require contextual adaptation to strengthen generalisability. Third, longitudinal and pilot implementation studies are needed to observe GenAI integration across full project lifecycles and generate deeper insights into long term governance assurance and performance implications particularly in relation to sustainability metrics and decision accountability. Finally, future work could prioritise governance and assurance mechanisms including model validation protocols bias auditing transparency frameworks and human in the loop decision structures to ensure trustworthy sustainability aligned risk decisions

References

Abilio, R., Morais, F., Vale, G., Oliveira, C., Pereira, D. and Costa, H., 2015. Applying information retrieval techniques to detect duplicates and to rank references in the preliminary phases of systematic: Literature reviews. CLEI Electronic Journal, 18(2), pp.3-3.

Abioye, S.O., Oyedele, L.O., Akanbi, L., Ajayi, A., Delgado, J.M.D., Bilal, M., Akinade, O.O. and Ahmed, A., 2021. Artificial intelligence in the construction industry: A review of present status, opportunities and future challenges. Journal of Building Engineering, 44, p.103299.

Adeva, J.G., Atxa, J.P., Carrillo, M.U. and Zengotitabengoa, E.A., 2014. Automatic text classification to support systematic reviews in medicine. Expert Systems with Applications, 41(4), pp.1498-1508.

Adewale, B.A., Ene, V.O., Ogunbayo, B.F. and Aigbavboa, C.O., 2024. A Systematic Review of the Applications of AI in a Sustainable Building's Lifecycle. Buildings, 14(7), p.2137.

Afzal, F., Yunfei, S., Nazir, M. and Bhatti, S.M., 2021. A review of artificial intelligence-based risk assessment methods for capturing complexity-risk interdependencies: Cost overrun in construction projects. International Journal of Managing Projects in Business, 14(2), pp.300-328.

Akinosho, T.D., Oyedele, L.O., Bilal, M., Ajayi, A.O., Delgado, M.D., Akinade, O.O. and Ahmed, A.A., 2020. Deep learning in the construction industry: A review of present status and future innovations. Journal of Building Engineering, 32, p.101827.

Al Naqbi, K.K.M., Ojiako, U., Al-Mhdawi, M.K.S., Chipulu, M. and Dweiri, F.T., 2025. How different stakeholders perceive benefits, challenges, and barriers in the implementation of green technology projects. *Sustainability*, *17*(21), p.9849.

Aladag, H., 2023. Assessing the accuracy of ChatGPT use for risk management in construction projects. Sustainability, 15(22), p.16071.

Almashhour, R., Al-Mhdawi, M.K.S., Daghfous, A., Qazi, A. and Ojiako, U., 2025. Traditional to sustainable risk management in the construction industry: a systematic literature review. *International Journal of Managing Projects in Business*.

Al-Mhdawi, M.K.S. and O'Connor, A., 2026. Impact of sustainable safety climate on poor compliance with personal protective equipment in oil and gas construction projects: quantitative analysis and best sustainable practices. *Environmental Impact Assessment Review*, *117*, p.108211.

Al-Mhdawi, M.K.S., O'Connor, A. and Qazi, A., 2024a. Structural equation modeling and Fuzzy set theory: advancing risk assessment in oil and gas construction projects. Environmental Impact Assessment Review, 109, p.107622.

Al-Mhdawi, M.K.S., O'connor, A., Qazi, A., Rahimian, F. and Dacre, N., 2024b. Review of studies on risk factors in critical infrastructure projects from 2011 to 2023. Smart and Sustainable Built Environment.

Al-Mhdawi, M.K.S., Qazi, A., Alzarrad, A., Dacre, N., Rahimian, F., Buniya, M.K. and Zhang, H., 2023. Expert Evaluation of ChatGPT Performance for Risk Management Process Based on ISO 31000 Standard. Available at SSRN 4504409.

Al-Saffar, M.A., Darwish, A.S., Farrell, P.E.T.E.R. and Saffar, N.E.H.A.L., 2024. A Critical Analysis of Traditional and Ai-Based Risk Assessment Frameworks for Sustainable Construction Projects. J. Eng. Sci. Technol, 18, pp.35-54.

An Y., Li, H., Su, T. and Wang, Y., 2021. Determining uncertainties in AI applications in AEC sector and their corresponding mitigation strategies. Automation in Construction, 131, p.103883.

Anica-Popa, I., Rădulescu, C. and Vrîncianu, M., 2021. The integration of artificial intelligence in retail: benefits, challenges and a dedicated conceptual framework. Amfiteatru Economic, 23(56), pp.120-136.

Aramali, V., Cho, N., Pande, F., Al-Mhdawi, M.K.S., Ojiako, U. and Qazi, A., 2025. Generative AI in project management: Impacts on corporate values, employee perceptions, and organizational practices. *Project Leadership and Society*, p.100191.

Baduge, S.K., Thilakarathna, S., Perera, J.S., Arashpour, M., Sharafi, P., Teodosio, B., Shringi, A. and Mendis, P., 2022. Artificial intelligence and smart vision for building and construction 4.0: Machine and deep learning methods and applications. Automation in Construction, 141, p.104440.

Bandi, A., Adapa, P.V.S.R. and Kuchi, Y.E.V.P.K., 2023. The power of generative ai: A review of requirements, models, input–output formats, evaluation metrics, and challenges. Future Internet, 15(8), p.260.

Barcaui, A. and Monat, A., 2023. Who is better in project planning? Generative artificial intelligence or project managers? Project Leadership and Society, 4, p.100101.

Behrooz, H., Lipizzi, C., Korfiatis, G., Ilbeigi, M., Powell, M. and Nouri, M., 2023. Towards Automating the Identification of Sustainable Projects Seeking Financial Support: An AI-Powered Approach. Sustainability, 15(12), p.9701.

Bengesi, S., El-Sayed, H., Sarker, M.K., Houkpati, Y., Irungu, J. and Oladunni, T., 2024. Advancements in Generative AI: A Comprehensive Review of GANs, GPT, Autoencoders, Diffusion Model, and Transformers. IEEE Access.

Boinot, L., Diaz, J., Feuerpeil, S., Manoury, D. and Rao, G., 2023. Algorithms smarter than experts? AI methods applied to assessment of environmental risk of World Bank projects. International Journal of Sustainable Development, 26(2), pp.71-85.

Boughaba, A. and Bouabaz, M., 2020. Identification and risk management related to construction projects. Advances in Computational Design, 5(4), pp.445-465.

Bragança, L., Vieira, S.M. and Andrade, J.B., 2014. Early stage design decisions: the way to achieve sustainable buildings at lower costs. The scientific world journal, 2014(1), p.365364.

Brennan, S.E. and Munn, Z., 2021. PRISMA 2020: a reporting guideline for the next generation of systematic reviews. JBI evidence synthesis, 19(5), pp.906-908.

Caron, F. and Caron, F., 2013. Large Engineering Projects: The Oil and Gas Case. Managing the Continuum: Certainty, Uncertainty, Unpredictability in Large Engineering Projects, pp.11-14.

Celik, A. and Eltawil, A.M., 2024. At the Dawn of Generative AI Era: A tutorial-cum-survey on new frontiers in 6G wireless intelligence. IEEE Open Journal of the Communications Society.

Chenya, L., Aminudin, E., Mohd, S. and Yap, L.S., 2022. Intelligent risk management in construction projects: Systematic Literature Review. IEEE Access.

Chidolue, O., Ohenhen, P.E., Umoh, A.A., Ngozichukwu, B., Fafure, A.V. and Ibekwe, K.I., 2024. Green data centers: sustainable practices for energy-efficient it infrastructure. Engineering Science & Technology Journal, 5(1), pp.99-114.

Choi, S.W., Lee, E.B. and Kim, J.H., 2021. The engineering machine-learning automation platform (emap): A big-data-driven ai tool for contractors' sustainable management solutions for plant projects. Sustainability, 13(18), p.10384.

Chou, J.S., Chong, P.L. and Liu, C.Y., 2024. Deep learning-based chatbot by natural language processing for supportive risk management in river dredging projects. Engineering Applications of Artificial Intelligence, 131, p.107744.

Cooke-Davies, T.J. and Arzymanow, A., 2003. The maturity of project management in different industries: An investigation into variations between project management models. International Journal of Project Management, 21(6), pp.471-478.

Costantino, F., Di Gravio, G. and Nonino, F., 2015. Project selection in project portfolio management: An artificial neural network model based on critical success factors. International Journal of Project Management, 33(8), pp.1744-1754.

Craig, C.D. and Kay, R., 2024, May. An Introduction to the AI in Education: Shaping Future Classrooms Conference Companion. In Artificial Intelligence in Education Conference: Shaping Future Classrooms. Ontario Tech University.

da Silva, J.A.T. and Daly, T., 2024. Against Over-reliance on PRISMA Guidelines for Meta-analytical Studies. Rambam Maimonides Medical Journal, 15(1).

Dacre, N., Yan, J., Frei, R., Al-Mhdawi, M.K.S. and Dong, H., 2024. Advancing sustainable manufacturing: a systematic exploration of industry 5.0 supply chains for sustainability, human-centricity, and resilience. Production Planning & Control, pp.1-30.

Decker, S.L., Aleman-Meza, B., Cameron, D. and Arpinar, I.B., 2007. Detection of bursty and emerging trends towards identification of researchers at the early stage of trends.

Deng, L., 2018. Artificial intelligence in the rising wave of deep learning: The historical path and future outlook [perspectives]. IEEE Signal Processing Magazine, 35(1), pp.180-177.

Dua, I.K. and Patel, P.G., 2024. *Optimizing Generative AI Workloads for Sustainability: Balancing Performance and Environmental Impact in Generative AI*. Springer Nature.

Dulam, N., Gade, K.R. and Gosukonda, V., 2023. Generative AI for Data Augmentation in Machine Learning. Journal of AI-Assisted Scientific Discovery, 3(2), pp.665-688.

Dwivedi, Y.K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A. and Galanos, V., 2021. Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. International journal of information management, 57, p.101994.

Eacersall, D., Pretorius, L., Smirnov, I., Spray, E., Illingworth, S., Chugh, R., Strydom, S., Stratton-Maher, D., Simmons, J., Jennings, I. and Roux, R., 2024. Navigating Ethical Challenges in Generative AI-Enhanced Research: The ETHICAL Framework for Responsible Generative AI Use. arXiv preprint arXiv:2501.09021.

Eber, W., 2020. Potentials of artificial intelligence in construction management. Organization, technology & management in construction: an international journal, 12(1), pp.2053-2063.

Elseknidy, M., Al-Mhdawi, M.K.S., Mahammedi, C., Qazi, A., Ojiako, U. and Rahimian, F., 2025a. Mapping the landscape of risk management research in green building projects: a bibliometric review. *Urbanization, Sustainability and Society*, *2*(1), pp.407-437.

Elseknidy, M., Al-Mhdawi, M.K.S., Qazi, A., Ojiako, U., Mahammedi, C. and Rahimian, F.P., 2025b. Developing a sustainability-driven risk management framework for green building projects: A literature review. *Journal of Cleaner Production*, *519*, p.145891.

Ercolani, J.S., 2014. Cyclical activity and gestation lags in investment. The Manchester School, 82(5), pp.620-630.

Erfani, A. and Cui, Q., 2022. Predictive risk modelling for major transportation projects using historical data. Automation in Construction, 139, p.104301.

Erickson, B.J., 2021. Basic artificial intelligence techniques: machine learning and deep learning. Radiologic Clinics of North America, 59(6), pp.933-940.

Ewim, D.R.E., Ninduwezuor-Ehiobu, N., Orikpete, O.F., Egbokhaebho, B.A., Fawole, A.A. and Onunka, C., 2023. Impact of data centers on climate change: a review of energy efficient strategies. The Journal of Engineering and Exact Sciences, 9(6), pp.16397-01e.

Falkner, S., Klein, A. and Hutter, F., 2018. Practical hyperparameter optimization for deep learning.

Fridgeirsson, T.V., Ingason, H.T., Jonasson, H.I. and Gunnarsdottir, H., 2023. A Qualitative Study on Artificial Intelligence and Its Impact on the Project Schedule, Cost and Risk Management Knowledge Areas as Presented in PMBOK®. Applied Sciences, 13(19), p.11081.

Galvão, L.A., Haby, M.M., Chapman, E., Clark, R., Câmara, V.M., Luiz, R.R. and Becerra-Posada, F., 2016. The new United Nations approach to sustainable development post-2015: findings from four overviews of systematic reviews on interventions for sustainable development and health. Revista Panamericana de Salud Pública, 39, pp.157-165.

Gholizadeh, P., Esmaeili, B. and Goodrum, P., 2018. Diffusion of building information modeling functions in the construction industry. Journal of Management in Engineering, 34(2), p.04017060.

Gil de Zúñiga, H., Goyanes, M. and Durotoye, T., 2024. A scholarly definition of artificial intelligence (AI): advancing AI as a conceptual framework in communication research. Political communication, 41(2), pp.317-334.

Giraud, L., Zaher, A., Hernandez, S. and Akram, A.A., 2023. The impacts of artificial intelligence on managerial skills. International Journal of Construction Management, 32(3), pp.566-599.

Golovianko, M., Terziyan, V., Branytskyi, V. and Malyk, D., 2023. Industry 4.0 vs. Industry 5.0: Co-existence, transition, or a hybrid. Procedia Computer Science, 217, pp.102-113.

Gonzalez-Rodriguez, D. and Hernandez-Carrion, J.R., 2018. Self-Organized Linguistic Systems: From traditional AI to bottom-up generative processes. Futures, 103, pp.27-34.

Goralski, M.A. and Tan, T.K., 2020. Artificial intelligence and sustainable development. The International Journal of Management Education, 18(1), p.100330.

Grant, K.P. and Pennypacker, J.S., 2006. Project management maturity: An assessment of project management capabilities among and between selected industries. IEEE Transactions on Engineering Management, 53(1), pp.59-68.

Greif, L., Kimmig, A., El Bobbou, S., Jurisch, P. and Ovtcharova, J., 2024. Strategic view on the current role of AI in advancing environmental sustainability: a SWOT analysis. Discover Artificial Intelligence, 4(1), p.45.

Grimes, M., Von Krogh, G., Feuerriegel, S., Rink, F. and Gruber, M., 2023. From scarcity to abundance: Scholars and scholarship in an age of generative artificial intelligence. Academy of Management Journal, 66(6), pp.1617-1624.

Gupta, M., Akiri, C., Aryal, K., Parker, E. and Praharaj, L., 2023. From chatgpt to threatgpt: Impact of generative ai in cybersecurity and privacy. IEEE Access.

Gupta, P., Ding, B., Guan, C. and Ding, D., 2024. Generative AI: A systematic review using topic modelling techniques. Data and Information Management, p.100066.

Hannan, M.A., Al-Shetwi, A.Q., Ker, P.J., Begum, R.A., Mansor, M., Rahman, S.A., Dong, Z.Y., Tiong, S.K., Mahlia, T.I. and Muttaqi, K.M., 2021. Impact of renewable energy utilization and artificial intelligence in achieving sustainable development goals. Energy Reports, 7, pp.5359-5373.

Hao, L., Yang, L.Z. and Gao, J.M., 2014. The application of information diffusion technique in probabilistic analysis to grassland biological disasters risk. Ecological modelling, 272, pp.264-270.

Hashfi, M.I. and Raharjo, T., 2023. Exploring the challenges and impacts of artificial intelligence implementation in project management: A systematic literature review. International Journal of Advanced Computer Science and Applications, 14(9).

Holtzman, A., Buys, J., Du, L., Forbes, M. and Choi, Y., 2019. The curious case of neural text degeneration. arXiv preprint arXiv:1904.09751.

Howard J, Piacentino J, MacMahon K, Schulte P. Using systematic review in occupational safety and health. American Journal of Industrial Medicine. 2017 Nov;60(11):921-9.

Howard, B.E., Phillips, J., Tandon, A., Maharana, A., Elmore, R., Mav, D., Sedykh, A., Thayer, K., Merrick, B.A., Walker, V. and Rooney, A., 2020. SWIFT-Active Screener: Accelerated document screening through active learning and integrated recall estimation. Environment International, 138, p.105623.

Hua, H., Li, Y., Wang, T., Dong, N., Li, W. and Cao, J., 2023. Edge computing with artificial intelligence: A machine learning perspective. ACM Computing Surveys, 55(9), pp.1-35.

Ibrahim, M.I.M., 2016. Estimating the sustainability returns of recycling construction waste from building projects. Sustainable Cities and Society, 23, pp.78-93.

Jallow, H., Renukappa, S., Suresh, S. and Rahimian, F., 2023. Artificial Intelligence and the UK Construction Industry–Empirical Study. Engineering Management Journal, 35(4), pp.420-433.

Kar, A.K., Choudhary, S.K. and Singh, V.K., 2022. How can artificial intelligence impact sustainability: A systematic literature review. Journal of Cleaner Production, 376, p.134120.

Karakhan, A.A. and Gambatese, J.A., 2017. Identification, quantification, and classification of potential safety risk for sustainable construction in the United States. Journal of Construction Engineering and Management, 143(7), p.04017018.

Karakhan, A.A., 2016. LEED-certified projects: Green or sustainable?. Journal of Management in Engineering, 32(5), p.02516001.

Kazeem, K.O., Olawumi, T.O. and Osunsanmi, T., 2023. Roles of Artificial Intelligence and Machine Learning in Enhancing Construction Processes and Sustainable Communities. Buildings, 13(8), p.2061.

Khodabakhshian, A., Puolitaival, T. and Kestle, L., 2023. Deterministic and probabilistic risk management approaches in construction projects: A systematic literature review and comparative analysis. Buildings, 13(5), p.1312.

Kiani Mavi, R., Gengatharen, D., Kiani Mavi, N., Hughes, R., Campbell, A. and Yates, R., 2021. Sustainability in construction projects: a systematic literature review. Sustainability, 13(4), p.1932.

Kulkarni, P.S., Londhe, S.N. and Deo, M., 2017. Artificial neural networks for construction management: a review. Journal of Soft Computing in Civil Engineering, 1(2), pp.70-88.

Lakhanpal, S., Gupta, A. and Agrawal, R., 2014, March. On discovering most frequent research trends in a scientific discipline using a text mining technique. In Proceedings of the 2014 ACM Southeast Regional Conference (pp. 1-4).
Le, H.S., Lee, J.H. and Lee, H.K., 2014. Exploring current research topics and trends based on the keywords analysis in the leading information systems journals. Korea, 14(2), pp.161-180.
Leslie, D. and Rossi, F., 2023. ACM TechBrief: generative artificial intelligence.
Li, X., Yi, S., Cundy, A.B. and Chen, W., 2022. Sustainable decision-making for contaminated site risk management: A decision tree model using machine learning algorithms. Journal of Cleaner Production, 371, p.133612.
Liang, C.J., Le, T.H., Ham, Y., Mantha, B.R., Cheng, M.H. and Lin, J.J., 2024. Ethics of artificial intelligence and robotics in the architecture, engineering, and construction industry. Automation in Construction, 162, p.105369.
Liao, M., Lan, K. and Yao, Y., 2022. Sustainability implications of artificial intelligence in the chemical industry: A conceptual framework. Journal of industrial ecology, 26(1), pp.164-182.
Liengpunsakul, S., 2021. Artificial intelligence and sustainable development in China. The Chinese Economy, 54(4), pp.235-248.
Lishner, I. and Shtub, A., 2022. Using an artificial neural network for improving the prediction of project duration. Mathematics, 10(22), p.4189.
Lytras, M.D. and Chui, K.T., 2019. The recent development of artificial intelligence for smart and sustainable energy systems and applications. Energies, 12(16), p.3108.
Ma, J. and Lund, B., 2020. The evolution of LIS research topics and methods from 2006 to 2018: A content analysis. Proceedings of the Association for Information Science and Technology, 57(1), p.e241.
Maki-Tanila, A. and Webster, L., 2019. Heritability, SNP, inbreeding, dairy cattle, genomic selection—and other keywords. Journal of Animal Breeding and Genetics, 136(1), pp.1-2.
Manzoor, B., Othman, I., Durdyev, S., Ismail, S. and Wahab, M.H., 2021. Influence of artificial intelligence in civil engineering toward sustainable development—a systematic literature review. Applied System Innovation, 4(3), p.52.
McMillan, L. and Varga, L., 2022. A review of the use of artificial intelligence methods in infrastructure systems. Engineering Applications of Artificial Intelligence, 116, p.105472.
Metwally, A.B., Ali, S.A. and Mohamed, A.T., 2024, January. Thinking Responsibly About Responsible AI in Risk Management: The Darkside of AI in RM. In 2024 ASU International Conference in Emerging Technologies for Sustainability and Intelligent Systems (ICETSIS) (pp. 1-5). IEEE.
Minh, D., Wang, H.X., Li, Y.F. and Nguyen, T.N., 2022. Explainable artificial intelligence: a comprehensive review. Artificial Intelligence Review, pp.1-66.
Mishra A, Pareek RK, Kumar S, Varalakshmi S. A review of the current and future developments of artificial intelligence in the management and building sectors. Multidisciplinary Reviews. 2023;6.
Mohapatra, M., Phukan, A. and Madisetti, V.K., 2023. Generative Adversarial Network Based Approach towards Synthetically Generating Insider Threat Scenarios. Journal of Software Engineering and Applications, 16(11), pp.586-604.
Moher, D., Liberati, A., Tetzlaff, J., Altman, D.G. and Prisma Group, 2010. Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. International journal of surgery, 8(5), pp.336-341.
Moon, J., Noh, Y., Jung, S., Lee, J. and Hwang, E., 2023. Anomaly detection using a model-agnostic meta-learning-based variational auto-encoder for facility management. Journal of Building Engineering, 68, p.106099.
Mrówczyńska, M., Sztubecka, M., Skiba, M., Bazan-Krzywoszańska, A. and Bejga, P., 2019. The use of artificial intelligence as a tool supporting sustainable development local policy. Sustainability, 11(15), p.4199.

Muller, R., Locatelli, G., Holzmann, V., Nilsson, M. and Sagay, T., 2024. Artificial Intelligence and Project Management: Empirical Overview, State of the Art, and Guidelines for Future Research. Project Management Journal, p.87569728231225198.

Najafabadi, M.M.; Villanustre, F.; Khoshgoftaar, T.M.; Seliya, N.; Wald, R.; and Muharemagic, E. (2015). Deep learning applications and challenges in big data analytics. Journal of Big Data, 2(1),1-21.

Nishant, R., Kennedy, M. and Corbett, J., 2020. Artificial intelligence for sustainability: Challenges, opportunities, and a research agenda. International Journal of Information Management, 53, p.102104.

Nyoto, R.L.V., Devega, M. and Nyoto, N., 2024. Cyber Security Risks in the Rapid Development of Generative Artificial Intelligence: A Systematic Literature Review. CommiTech: Journal of Computational Intelligence and Informatics, 1(2), pp.57-66.

Nyqvist, R., Peltokorpi, A. and Seppänen, O., 2024. Can ChatGPT exceed humans in construction project risk management?. Engineering, Construction and Architectural Management, 31(13), pp.223-243.

Olanrewaju, A.L. (2022). An artificial neural network analysis of rework in sustainable buildings. IOP Conference Series: Earth and Environmental Science, 1101(2), 022003-022012.

Pan, Y. and Zhang, L., 2021. Roles of artificial intelligence in construction engineering and management: A critical review and future trends. Automation in Construction, 122, p.103517.

Papadonikolaki, E., Narayanan, V.V., Sankaran, S. and Clegg, S., 2025. The role of digitalization in project management. Project Leadership and Society, p.100184.

Parveen, R., 2018. Artificial intelligence in construction industry: Legal issues and regulatory challenges. International Journal of Civil Engineering and Technology, 9(13), pp.957-962.

Pati, D. and Lorusso, L.N., 2018. How to write a systematic review of the literature. HERD: Health Environments Research & Design Journal, 11(1), pp.15-30.

Pillai, V.S. and Matus, K.J., 2020. Towards a responsible integration of artificial intelligence technology in the construction sector. Science and Public Policy, 47(5), pp.689-704.

Podgorska, M., 2022. Challenges and perspectives in innovative projects focused on sustainable industry 4.0—A case study on polish project teams. *Sustainability*, *14*(9), p.5334.

Poh, C.Q., Ubeynarayana, C.U. and Goh, Y.M., 2018. Safety leading indicators for construction sites: A machine learning approach. Automation in construction, 93, pp.375-386.

Pun, C.S., Wang, L. and Wong, H.Y., 2020, May. Financial thought experiment: A GAN-based approach to vast robust portfolio selection. In Proceedings of the 29th International Joint Conference on Artificial Intelligence (IJCAI'20).

Rajaguru, P.P., Ademuwagun, L., Pierre-Louis, Y., Reddy, N.G. and Moreira, C.C., 2022. Moving beyond diversity: a scoping review of inclusion initiatives in the surgical workforce. Journal of the American College of Surgeons, 234(2), pp.203-213.

Regona, M., Yigitcanlar, T., Hon, C. and Teo, M., 2024. Artificial Intelligence and Sustainable Development Goals: Systematic Literature Review of the Construction Industry. Sustainable Cities and Society, p.105499.

Regona, M., Yigitcanlar, T., Hon, C.K. and Teo, M., 2023. Mapping Two Decades of AI in Construction Research: A Scientometric Analysis from the Sustainability and Construction Phases Lenses. Buildings, 13(9), p.2346.

Rezvani, S.M., Falcão, M.J., Komljenovic, D. and de Almeida, N.M., 2023. A systematic literature review on urban resilience enabled with asset and disaster risk management approaches and GIS-based decision support tools. Applied Sciences, 13(4), p.2223.

Robinson, K.A., Saldanha, I.J. and Mckoy, N.A., 2011. Development of a framework to identify research gaps from systematic reviews. Journal of clinical epidemiology, 64(12), pp.1325-1330.

Saka, A., Taiwo, R., Saka, N., Salami, B.A., Ajayi, S., Akande, K. and Kazemi, H., 2023. GPT models in construction industry: Opportunities, limitations, and a use case validation. Developments in the Built Environment, p.100300.

Shadbolt, N., 2022. “From So Simple a Beginning”: Species of Artificial Intelligence. Daedalus, 151(2), pp.28-42.

Singh, A., Dwivedi, A., Agrawal, D. and Singh, D., 2023. Identifying issues in adoption of AI practices in construction supply chains: towards managing sustainability. Operations Management Research, 16(4), pp.1667-1683.

Smith, C.J. and Wong, A.T., 2022, May. Advancements in artificial intelligence-based decision support systems for improving construction project sustainability: a systematic literature review. In Informatics (Vol. 9, No. 2, p. 43). MDPI.

Sony, M. and Naik, S., 2020. Critical factors for the successful implementation of Industry 4.0: a review and future research direction. Production Planning & Control, 31(10), pp.799-815.

Stanitsas, M., Kirytopoulos, K. and Leopoulos, V., 2021. Integrating sustainability indicators into project management: The case of construction industry. Journal of Cleaner Production, 279, p.123774.

Strube, D., Daase, C. and Schietzel-Kalkbrenner, J., 2024. Applications of Artificial Intelligence in Sustainability Assessment and Risk Management in European Banking. In FEMIB (pp. 25-32).

Sung, J.J., Stewart, C.L. and Freedman, B., Artificial intelligence in health care: Preparing for the Fifth Industrial Revolution. MJA. 2020; 213 (6): 253-55. e1.

Székely, B., Késmárki-Gally, S.E. and Lakner, Z., 2025. Hybrid Project Management: Scoping review. Project Leadership and Society, p.100182.

Taneja, S., Jaggi, P., Jewandah, S. and Ozen, E., 2022. Role of Social Inclusion in Sustainable Urban Developments: An Analyse by PRISMA. Journal homepage: http://iieta. org/journals/ijdne, 17(6), pp.937-942.

Taye, M., 2016. Assessment of time and cost overruns in construction projects (case study at defense construction enterprise) (Doctoral dissertation, ST. MARY'S UNIVERSITY).

Tiza, M.T., 2022. Sustainability in the civil engineering and construction industry: A review. Journal of Sustainable Construction Materials and Technologies, 7(1), pp.30-39.

Trifu, A., Smîdu, E., Badea, D.O., Bulboacă, E. and Haralambie, V., 2022. Applying the PRISMA method for obtaining systematic reviews of occupational safety issues in literature search. In MATEC Web of Conferences (Vol. 354, p. 00052). EDP Sciences.

Truby, J., 2020. Governing artificial intelligence to benefit the UN sustainable development goals. Sustainable Development, 28(4), pp.946-959.

Tumpa, R.J., Ahmad, T., Naeni, L.M. and Kujala, J., 2024. Computer-based games in project management education: A review. Project Leadership and Society, 5, p.100130.

Turek, J., Ocicka, B., Rogowski, W. and Jefmański, B., 2023. The role of Industry 4.0 technologies in driving the financial importance of sustainability risk management. Equilibrium. Quarterly Journal of Economics and Economic Policy, 18(4), pp.1009-1044.

Uriarte-Gallastegi, N., Arana-Landín, G., Landeta-Manzano, B. and Laskurain-Iturbe, I., 2024. The Role of AI in Improving Environmental Sustainability: A Focus on Energy Management. Energies, 17(3), p.649.

Vettori, V., Lorini, C., Milani, C. and Bonaccorsi, G., 2019. Towards the implementation of a conceptual framework of food and nutrition literacy: Providing healthy eating for the population. International journal of environmental research and public health, 16(24), p.5041.

Wach, K., Duong, C.D., Ejdys, J., Kazlauskaitė, R., Korzynski, P., Mazurek, G., Paliszkiewicz, J. and Ziemba, E., 2023. The dark side of generative artificial intelligence: A critical analysis of controversies and risks of ChatGPT. Entrepreneurial Business and Economics Review, 11(2), pp.7-30.

Wang,R. (2023).Review of Generative Models.Applied and Computational Engineering,8,524-529.

Wankhede, V.A., Agrawal, R., Kumar, A., Luthra, S., Pamucar, D. and Stević, Ž., 2024. Artificial intelligence an enabler for sustainable engineering decision-making in uncertain environment: a review and future propositions. Journal of Global Operations and Strategic Sourcing, 17(2), pp.384-401.

Waqar, A., Othman, I., Shafiq, N. and Mansoor, M.S., 2023. Applications of AI in oil and gas projects towards sustainable development: a systematic literature review. Artificial Intelligence Review, 56(11), pp.12771-12798.

Wu, D., Olson, D.L. and Dolgui, A., 2017. Artificial intelligence in engineering risk analytics. Engineering applications of artificial intelligence, 65, pp.433-435.

Wu, J. and Shang, S., 2020. Managing uncertainty in AI-enabled decision making and achieving sustainability. Sustainability, 12(21), p.8758.

Yaseen, Z.M., Ali, Z.H., Salih, S.Q. and Al-Ansari, N., 2020. Prediction of risk delay in construction projects using a hybrid artificial intelligence model. Sustainability, 12(4), p.1514.

Yigitcanlar, T., Desouza, K.C., Butler, L. and Roozkhosh, F., 2020. Contributions and risks of artificial intelligence (AI) in building smarter cities: Insights from a systematic review of the literature. Energies, 13(6), p.1473.

Yoshida, S. and Tanaka, S., 2021. Artificial intelligence for the detection of gastric precancerous conditions using image-enhanced endoscopy: What kind of abilities are required for application in real-world clinical practice? Gastrointestinal Endoscopy, 94(3), pp.549-550.

Zavadskas, E.K., Šaparauskas, J. and Antucheviciene, J., 2018. Sustainability in construction engineering. Sustainability, 10(7), p.2236.

Zhang, H., Song, M. and He, H., 2020. Achieving the success of sustainability development projects through big data analytics and artificial intelligence capability. Sustainability, 12(3), p.949.

Zhang, L., Wu, X., Skibniewski, M.J., Zhong, J. and Lu, Y., 2014. Bayesian-network-based safety risk analysis in construction projects. Reliability Engineering & System Safety, 131, pp.29-39.

Zhou, H., Tang, S., Huang, W. and Zhao, X., 2023. Generating risk response measures for subway construction by fusion of knowledge and deep learning. Automation in Construction, 152, p.104951.

Zou, Y., Kiviniemi, A. and Jones, S.W., 2017. Retrieving similar cases for construction project risk management using Natural Language Processing techniques. Automation in construction, 80, pp.66-76.

Appendix A. Key studies exploring GenAI-driven project risk management:Theories, Drivers, Impact and Challenges

No.	Paper	Source	Title	Drives	Impact	Challenges	GenAI Theory
1	Liang et al., (2024)	Journal	Automation in Construction		✓	✓	✓
2	Chou et al., (2024)	Journal	Engineering Applications of Artificial Intelligence		✓	✓	✓
3	Costantino (2015)	Journal	International Journal of Project Management		✓		✓
4	Kulkarni et al. (2017)	Journal	Journal of Soft Computing in Civil Engineering	✓	✓	✓	✓
5	Wu et al. (2017)	Journal	Engineering Applications of Artificial Intelligence		✓	✓	✓
6	Zou et al. (2017)	Journal	Automation in Construction		✓	✓	✓
7	Poh et al. (2018)	Journal	Automation in Construction		✓	✓	
8	Parveen (2018)	Journal	IJCIET		✓		
9	Boughaba, and Bouabaz (2020)	Journal	Advances in Computational Design		✓		✓
10	Eber (2020)	Journal	Organization, Technology, Management in Construction		✓	✓	✓
11	Yaseen et al. (2020)	Journal	Sustainability (Switzerland)		✓		✓
12	Pillai and Matus (2020)	Journal	Science and Public Policy		✓		✓
13	Abioye et al. (2021)	Journal	Journal of Building Engineering		✓	✓	✓
14	Pan and Zhang (2021)	Journal	Automation in Construction	✓	✓	✓	✓
15	Afzal et al. (2021)	Journal	International Journal of Managing Projects in Business		✓		✓
16	An et al. (2021)	Journal	Automation in Construction		✓	✓	✓
17	Choi, et al. (2021)	Journal	Sustainability (Switzerland)	✓	✓	✓	✓
18	Regona et al. (2022)	Journal	Buildings		✓	✓	
19	Adewale et al., (2024)	Journal	Buildings	✓	✓	✓	✓
20	Akinosho et al., (2020)	Journal	Journal of Building Engineering		✓	✓	✓
21	Aladag (2023)	Journal	Sustainability (Switzerland)		✓		✓
22	Al-Saffar et al., (2024)	Journal	Journal of Engineering Science and Technology	✓	✓	✓	✓
23	Baduge et al., (2022)	Journal	Automation in Construction			✓	
24	Bandi et al., (2023)	Journal	Future Internet			✓	✓
25	Behrooz et al., (2023)	Journal	Sustainability (Switzerland)	✓	✓	✓	✓
26	Boinot et al., (2023)	Journal	International Journal of Sustainable Development	✓	✓		✓
27	Chenya et al., (2023)	Journal	IEEE Access		✓		✓
28	Erfani and Cui (2022)	Journal	Automation in Construction		✓		✓

29	Fridgeirsson et al., (2023)	Journal	Applied Sciences (Switzerland)		✓	✓	✓
30	Giraud et al., (2023)	Journal	Journal of Decision Systems		✓		
31	Goralski and Tan (2020)	Journal	International Journal of Management Education	✓	✓		
32	Greif et al., (2024)	Journal	Discover Artificial Intelligence	✓	✓	✓	✓
33	Gupta et al., (2023)	Journal	IEEE Access		✓	✓	✓
34	Hannan et al., (2021)	Journal	Energy Reports	✓	✓		
35	Hashfi and Raharjo (2023)	Journal	IJACSA			✓	✓
36	Jallow et al., (2023)	Journal	EMJ - Engineering Management Journal		✓	✓	
37	Kar et al., (2022)	Journal	Journal of Cleaner Production	✓	✓		
38	Kazeem et al (2023)	Journal	Buildings	✓	✓	✓	✓
39	Li et al., (2022)	Journal	Journal of Cleaner Production		✓		✓
40	Liao et al., (2022)	Journal	Journal of Industrial Ecology	✓	✓	✓	
41	Manzoor et al., (2021)	Journal	Applied System Innovation		✓	✓	✓
42	McMillan and Varga (2022)	Journal	Engineering Applications of Artificial Intelligence			✓	✓
43	Metwally et al., (2024)	Conference	ASU Conference, ICETSIS 2024			✓	
44	Mishra et al., (2023)	Journal	Multidisciplinary Reviews		✓		
45	Muller et al., (2024)	Journal	Project Management Journal		✓	✓	✓
46	Najafabadi et al., (2015)	Journal	Journal of Big Data		✓	✓	✓
47	Nyqvist et al., (2024)	Journal	Engineering, Construction and Architectural Management		✓	✓	✓
48	Olanrewaju (2022)	Conference	IOP Conference Series: Earth and Environmental Science		✓		
49	Saka et al., (2023)	Journal	Developments in the Built Environment		✓	✓	✓
50	Singh et al., (2023)	Journal	Operations Management Research	✓	✓		
51	Smith and Wong (2022)	Journal	Informatics	✓	✓	✓	✓
52	Strube et al., (2024)	Conference	FEMIB 2024 conference		✓	✓	
53	Turek et al., (2023)	Journal	Equilibrium QJEEP	✓	✓	✓	✓
54	Uriarte et al., (2024)	Journal	Energies	✓	✓	✓	✓
55	Wankhede et al., (2024)	Journal	Journal of Global Operations and Strategic Sourcing		✓		
56	Waqar et al., (2023)	Journal	Artificial Intelligence Review		✓		
57	Wu and Shang (2020)	Journal	Sustainability (Switzerland)		✓		

58	Yigitcanlar et al., (2020)	Journal	Energies		✓		
59	Zhang et al., (2020)	Journal	Sustainability (Switzerland)		✓		
60	Zhang et al., (2014)	Journal	Reliability Engineering and System Safety		✓	✓	
61	Zhou et al., (2024)	Journal	Automation in Construction		✓	✓	✓
62	Regona et al., (2024)	Journal	Sustainable Cities and Society	✓	✓	✓	✓
63	Lytras and Chui (2019)	Journal	Energies	✓	✓		
64	Mrówczyńska et al., (2019)	Journal	Sustainability (Switzerland)	✓			✓
65	Liengpunsakul (2021)	Journal	Chinese Economy	✓			✓
66	Truby (2020)	Journal	Sustainable Development	✓	✓	✓	✓

Highlights

- Conducts a systematic literature review (SLR) of 66 peer-reviewed articles on GenAI-driven risk management for sustainable development projects, published between 2014 and 2024.
- Identifies key drivers of GenAI adoption in project risk management, including enhanced predictive accuracy, regulatory compliance, and sustainability objectives.
- Examines major challenges and risks of integrating GenAI into project risk management, such as legal constraints, ethical concerns, resource limitations, skills gaps, and technical complexities.
- Demonstrates GenAI's impact on improving projects risk management across environmental, social, and economic sustainability in construction projects.
- Develops a GenAI-driven risk management framework to support sustainable development projects.

Declaration of Interest Statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this study.