An Analytical Framework for Evaluating Generative Intelligence Risks in Sustainable Construction

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Abstract

This study investigates the emerging risks associated with integrating Generative Artificial Intelligence (GenAI) into risk management (RM) within sustainable construction projects (SCPs). A four-stage methodology was adopted: (1) a systematic literature review to identify GenAI-related risk factors; (2) the development of a multi-criteria assessment model to establish evaluation criteria; (3) a structured survey involving 80 construction experts to assess the identified risks; and (4) the application of a fuzzy logic-based model to quantify and rank their significance. Thirty risk factors were identified and grouped into five categories: input quality, technological adaptability, ethical and governance, information integrity, and financial risks. Fuzzy analysis highlighted human error, data unavailability, insufficient training, data breaches, and lack of awareness as the most critical risk factors. The study presents a novel, fuzzy logic-based risk assessment framework tailored explicitly to GenAI adoption in sustainable construction, providing enhanced decision-making capabilities in uncertain environments. It provides actionable insights for project managers and policymakers to prioritise and mitigate key risks, while also supporting responsible GenAI implementation. As one of the first studies to systematically examine these risks, it advances the discourse on AI integration in the built environment. It presents a replicable model for future assessments, encouraging context-sensitive research and contributing to the broader digital transformation of sustainable construction.

Keywords: *Generative intelligence; Risk prioritization; Decision support; Expert evaluation; Fuzzy modelling; Sustainable construction.*

1. Introduction

There is no doubt that artificial intelligence (AI) has become an integral part of projects and a valuable partner to project managers throughout the project life cycle (Mohawesh et al., 2025; Bento et al., 2022). Recently AI has significantly evolved, leveraging massive datasets to train machines and generate new materials (Lachhab et al., 2018). This advancement has accompanied in a new period of generative artificial intelligence (GenAI), characterised using complex algorithms and deep learning approaches (Mohamed et al., 2025a). These methods enable machines to analyse, process, and derive insights from vast amounts of data. GenAI employs various approaches, including neural networks, natural language processing (NLP), reinforcement learning, generative adversarial networks (GANs), and transformers, to achieve its current capabilities (Bengesi et al., 2024). This transformative technology has found applications in diverse engineering domains, including construction management, with a particular focus on risk management (Chenya et al., 2022).

Many organisations now utilise advanced risk management tools that leverage GenAI to enhance traditional risk management processes, including risk identification, assessment, and control throughout project execution (Al-Mhdawi et al., 2023a). These tools enable project managers to make informed, data-driven decisions, optimise strategies for mitigating risks, and identify opportunities to improve project outcomes (Regona et al., 2022; Chenya et al., 2022). Despite significant advancements in developing and testing GenAI models across various engineering disciplines, there remains a notable lack of consensus on the risks associated with deploying these technologies in risk management (RM) specially within the context of sustainable construction projects (SCPs) (Mohamed et al., 2025b). SCPs refer to construction activities that are designed, planned, and executed to minimise negative environmental, social, and economic impacts while maximising long-term benefits for society and the environment (Kibert, 2016). In simple terms, sustainable construction is about building in a way that protects the environment, supports the community, and uses resources wisely — both during construction and in the building's operational phase (Zuo and Zhao, 2014). Giesekam et al. (2016), Azhar et al. (2011) identifies key features of sustainable construction as including the use of eco-friendly materials, energy efficiency (e.g., solar panels and smart systems), water conservation strategies, waste reduction practices, green building design, attention to occupant health and well-being, efforts to reduce carbon footprints, and sustainable site management that preserves biodiversity and reduces land disturbance.

There is no doubt the uncertainty is exacerbated by the diverse nature of the construction industry (Aladag, 2023), which spans a wide range of project types, from residential buildings to large-scale infrastructure projects, each with unique and technological requirements (Anysz et al., 2021; Parveen, 2018). Furthermore, RM in SCPs involves a complex network of stakeholders, including project managers, consultants, contractors, and safety officers, all of whom bring differing expectations and experiences with GenAI in managing risks associated with environment, society and economy. These divergent perspectives often lead to conflicting priorities and ambiguity regarding the perceived benefits and emerging risks associated with GenAI technologies (Chenya et al., 2022). Therefore, the adoption of GenAI in RM for SCPs is further complicated by the variability of regulatory environments across regions, which influence the feasibility and scope of GenAI applications (Taiwo et al., 2024). This complex and dynamic environment makes the construction industry an ideal subject for exploring the potential risks of GenAI in RM of sustainable project for ensuring project success, operational efficiency, cost management, and worker safety (Regona et al., 2022).

However, integrating GenAI into RM of SCPs presents numerous risks that have not been thoroughly addressed in existing literature (Mohamed et al., 2024a). These risks can be categorised into themes such as input quality risks, technological adaptability risks, ethical and governance risks, information integrity risks, and financial risks. For instance, input quality risks arise from inaccurate, biased, or insufficient data used to train GenAI models, which can lead to flawed risk assessments (Afzal et al., 2021). While technological adaptability risks concern the integration challenges of GenAI tools within existing RM systems, including compatibility issues and the need for infrastructure upgrades (Parveen, 2018; An et al., 2021). Additionally, Aladag (2023) highlighted the ethical and governance risks include concerns around transparency, accountability, data privacy, and compliance with legal standards. Information integrity risks involve the potential for GenAI to produce hallucinated, misleading, or inconsistent outputs, thereby compromising decision reliability. Lastly, Pillai and Matus (2020) and Regona et al., (2022) revealed the financial risks relate to the high implementation costs, long-term maintenance, and possible economic inefficiencies if the technology underperforms. This categorisation provides a thematic overview of the key risks examined throughout the study, beyond the specific outputs of the systematic literature review.

While a substantial body of literature has explored the capabilities, benefits, and comparative performance of GenAI in various aspects of construction management, only a limited subset has addressed the risks and vulnerabilities associated with its integration into RM. Most previous studies have predominantly focused on the advantages of GenAI, such as its ability to enhance predictive accuracy, automate data processing, and support real-time decision-making. For instance, Pan, and Zhang (2021) investigated the implementation of GenAI for automating construction project documentation and forecasting potential delays, emphasising its efficiency in handling unstructured data, and improving overall project responsiveness. Similarly, Prebanic and Vukomanovic (2021) examined the use of GenAI-enabled chatbots in facilitating communication among project stakeholders, finding notable improvements in stakeholder engagement and information flow. Another study by Al-Mhdawi et al. (2023a) compared GenAI-driven risk identification models with traditional expert-based systems, concluding that the GenAI-powered models offered superior performance in recognising early-stage hazards and uncertainties.

Despite these advancements, there is a notable gap in literature regarding the risks that accompany GenAI integration into RM processes in SCPs. While a few recent works, such as Mohamed et al. (2025b), have begun to highlight this underexplored dimension, they remain exceptions rather than the norm. These emerging studies highlight a range of risks, including dependencies on data quality, ethical and legal uncertainties, and integration challenges with existing systems. However, few investigations have sought to categorise these risks into coherent themes or evaluate their relative significance within the context of SCPs. This gap underlines the urgent need for a comprehensive, empirically grounded exploration of GenAI-related risks in RM of SCPs not only to identify and understand the nature of these risks, but also to quantify their impact in a manner that supports informed decision-making based on their impact and potential consequences.

To this end, the aim of this research is to explore the critical risks associated with the integration of GenAI into RM in SCPs, with a focus on their identification, categorisation, and prioritisation based on empirical significance assessment, to support effective decision-making and risk mitigation strategies. Accordingly, the associated objectives are: (1) to identify the key risks encountered by organisations when implementing GenAI within RM in SCPs, (2) to categorise these risks into coherent groups, and (3) to prioritise the identified risks based on their significance using a structured multi-criteria decision-making approach. Ultimately, the findings are anticipated to enhance project managers' and decision-makers' understanding of GenAI-related risks into RM within SCPs, enabling them to allocate resources efficiently, mitigate high-impact risks, and ultimately improve the effectiveness of GenAI integration. The contributions of this research can be outlined as follows:

1. We identified and systematically categorised 30 key risk factors associated with the integration of GenAI into RM for SCPs. These were classified based on their sources into five thematic categories: input quality-related, technological adaptability-related, ethical and governance-related, information integrity-related, and financial risks-related. This categorisation provides a comprehensive risk landscape and offers actionable insights for construction practitioners, enabling them to anticipate and address potential GenAI-related threats in digitalised project environments. In particular, it supports the early identification of data-driven and ethical vulnerabilities that may compromise risk assessments, stakeholder trust, and project outcomes. Academically, this study contributes to closing a significant research gap by systematically examining the often-overlooked risks of GenAI adoption in the sustainable built environment.
2. We developed a novel multi-criteria hierarchical risk quantification model based on fuzzy set theory to assess the significance of identified Gen AI risks for SCPs. The model employs fuzzy logic controllers to evaluate key risk dimensions—probability, impact, detectability, and exposure—using twelve sub-criteria. To address the inherent subjectivity in expert assessments, linguistic judgments are systematically translated into numerical outputs, which enhances the model's precision and reduces inconsistencies often found in traditional evaluation methods. This approach is particularly valuable in the context of GenAI, where risk factors tend to be vague, interdependent, and difficult to quantify using conventional tools. Through its capacity to manage imprecision and reflect the variability of human reasoning, the model offers a robust and adaptable framework for risk assessment in SCPs. As data-driven decision-making becomes increasingly

central to managing complex technological risks, the model's relevance and practical utility are especially pronounced.

The remainder of the paper is organized as follows: Section 2 presents the adopted research methodology. Section 3 discusses the results and their implications. Finally, Section 4 concludes the study and outlines its practical and theoretical contributions.

2. Methodology

The research adopted a four-stage, multi-method approach to systematically identify, assess, and quantify the risks associated with integrating GenAI into the risk management of SCPs. In the first stage, a systematic literature review (SLR) was conducted to identify potential risks. The second stage involved a focus group session with industry experts to establish appropriate assessment criteria for evaluating each identified risk. In the third stage, a survey was administered, allowing participants to assess the significance of each criterion. Finally, in the fourth stage, the survey data were analysed using fuzzy set theory to develop a risk assessment model capable of quantifying the level of significance of each risk. The model's findings were subsequently validated through a follow-up expert focus group session.

Adopting a multi-method research approach offers significant advantages by enhancing both the depth and breadth of analysis (Al-Mhdawi et al., 2024a; Almalki, 2016). This methodological pluralism as shown in Figure 1 captures the complexity of the subject matter, providing a comprehensive framework for data interpretation (Hantrais, 2014). Similar methodologies have been employed in studies focused on risk identification and evaluation, such as those conducted by Al-Mhdawi et al. (2025), Al-Mhdawi et al. (2022), and Elnaggar and Elhegazy (2022).

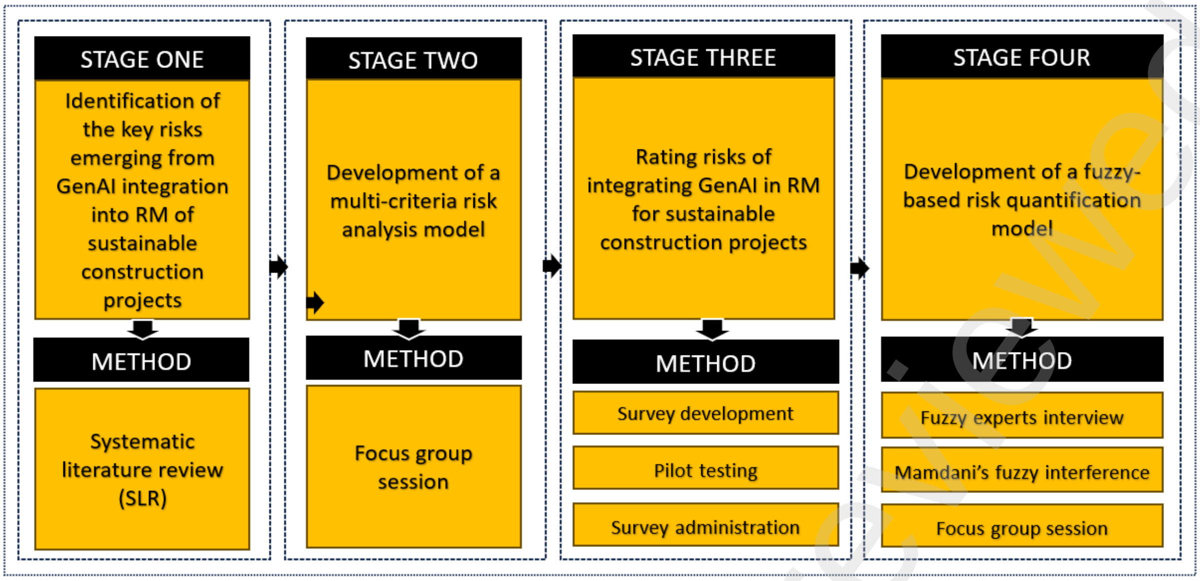

Figure 1. Adopted research methodology

Stage One: Identification of the key risks emerging from GenAI integration into RM of SCPs

This stage adopts a structured, three-step methodology for literature collection and analysis, designed to thoroughly examine existing studies and identify the key risks associated with integrating GenAI into RM in SCPs. The first step involves identifying relevant databases and journals to establish a robust foundation for the literature search. The second step entails strategically selecting articles using targeted keywords to ensure the inclusion of the most pertinent studies. Lastly, the third step focuses on conducting a systematic content analysis to extract valuable insights. This approach is guided by frameworks outlined in several risk management studies, particularly those by Al-Mhdawi et al. (2025), Al-Mhdawi et al. (2024b), and Siraj and Fayek, (2019).

Database and journal identification

In this research, the Scopus database was selected due to its extensive coverage of relevant research disciplines and its established use in similar literature-based studies within the field of construction management. The target journals for this study were chosen based on the following criteria: (1) they must be published in English, (2) they must have a minimum impact factor of 1.0, and (3) they must be ranked in the top quartile of the Scopus database, reflecting their substantial influence on advancements in construction management research.

Keyword identification and article selection

In this step, a comprehensive search was performed using the title, abstract, and keyword (T/A/K) fields within the Scopus search engine. The search keywords included "GenAI risks", "GenAI", "GenAI in RM", and "GenAI in sustainable construction project management". Articles containing these terms in the title, abstract, or keywords were considered to meet the preliminary inclusion criteria for further analysis. These keywords were carefully chosen to encompass a wide range of studies addressing the risks and applications of GenAI in RM for SCPs and related fields. The search results were then refined by removing duplicate entries, irrelevant studies, and papers that did not provide a substantive focus on the intersection of GenAI and RM in SCPs.

Content analysis

Hsieh and Barman et al. (2021) outline three approaches to content analysis: conventional, directed, and summative. This study adopted the conventional approach, a data-driven, open-ended method that allows categories to emerge organically without the constraints of predefined frameworks (Blomkvist, 2015). This approach, suitable for both qualitative and quantitative analysis, is particularly well-suited for investigating the emerging integration of GenAI into RM for SCPs, as it facilitates the extraction of detailed themes directly from the data (Kibiswa, 2019). Unlike directed analysis, it avoids limitations imposed by existing theories, fostering a rich and context-specific understanding (Hsieh and Shannon, 2005; Krippendorff, 2018). Using this method, the study systematically refined an initial pool of 471 papers to 55, identifying key risks and categories associated with integrating GenAI in RM for SCPs.

Stage Two: Development of a multi-criteria risk analysis model

Failure Mode and Effects Analysis (FMEA) is a widely applied risk assessment technique that evaluates the significance of risks by analysing three key factors: the probability level (PL) of occurrence, the impact level (IL) on project objectives, and the detectability level (DL) of the risk (Kritsky et al., 2018). This approach is extensively used across various engineering and construction fields (Alvand et al., 2023; Zhang et al., 2024). To develop the proposed multi-criteria risk analysis model based on IL, PL, and DL, a Delphi technique was conducted internally among the authors. This approach leveraged the authors' combined expertise in construction risk management and their prior research experience in developing fuzzy-based risk assessment models (Al-Mhdawi et al., 2024a; Mahammedi et al., 2020; Mohamed et al 2024). Two Delphi rounds were performed, allowing iterative review and refinement of the model structure to ensure logical consistency and domain relevance.

The impact dimension was categorised into two main groups project-related impacts, which include the impact on project cost (*ipc*), schedule (*ips*), and quality (*ipq*); and organisational impacts, which include the impact on decision-making (idm) and organisational reputation (*ior*). A similar structuring was applied to the probability criterion, which was assessed based on the availability of expertise (*ae*), availability of assets (*aa*), and the organisation's technological maturity (*otm*). For detectability, the relevant factors included ea, the presence of continuous monitoring mechanisms (acm), and the level of exposure, which was further informed by the risk duration (*rd*) and frequency of occurrence (*fo*). This methodological framework aligns with validated practices from previous fuzzy risk assessment studies (Al-Mhdawi et al., 2022; Al-Mhdawi et al., 2023b). the model ensures that the developed Risk–Probability, Impact, and Detectability (R-PID) model offers a context-specific and reliable tool for evaluating GenAI-related risks in sustainable construction projects. The overall fuzzy risk number (F-RN) is derived using the formula:

$$R = DL \times PL \times IL \quad \text{............. (1)}$$

Stage Three: Rating risks of integrating GenAI in RM for SCPs

In this stage, the authors employed a questionnaire survey instrument for data collection, as it enables respondents to provide information in a structured and standardised format, facilitating systematic data analysis and comparison while also offering a level of anonymity and confidentiality, which can encourage more honest and candid responses (Bird, 2019; Chartres et al., 2019).

Survey development

The authors developed a questionary survey to evaluate the significance of risks associated with integrating GenAI into RM for SCPs, as identified through the SLR. To quantify risk significance, respondents assessed each risk based on four key criteria: (1) the probability of occurrence, which measured the likelihood of the risk arising based on factors such as *ea, aa, and otm*; (2) the impact on project and organisation, including *ipc, ips, ipq, idm*, and *ior*; (3) the detectability of the risks, based on *ea, acm* and the exposure level which could be measure through evaluating risk *fo* and *rd*, which considered the duration and frequency of the risk during the project lifecycle. The survey consisted of two sections. The first section collected information from respondents, including their roles in construction field, years of experience, educational background and level of experience with GenAI in project management. The second section required respondents to assign relative weights to the identified risks. To facilitate this assessment, a five-point Likert scale was adopted, ranging from 1 (Very Low - V.L) to 5 (Very High - V.H). This scale enabled respondents to systematically evaluate the significance of each risk based on predefined assessment criteria, ensuring consistency and comparability in the collected data.

Survey pilot testing

Pilot testing is a critical preliminary step in survey-based research used to evaluate the reliability, validity, and overall quality of a questionnaire before deploying it on a larger scale. It ensures that survey items are clearly understood, appropriately worded, and capable of capturing the intended data, thereby improving the instrument's overall robustness and response accuracy (Saunders et al., 2019; Bryman, 2016). Conducting a pilot also helps identify potential ambiguities that may affect data collection and respondent experience. In this study, a pilot test was conducted with 10 construction experts from the UK to assess the clarity and effectiveness of the developed questionnaire. Table 1 presents participants' years of experience, industry roles, and educational backgrounds. Based on the feedback received, minor revisions were made to enhance the precision and relevance of the survey. These included adding a new question to assess respondents' experience with using GenAI in project management and renaming certain criteria to improve clarity and ease of understanding during the risk evaluation process.

Table 1. Pilot test profile of participants

No. of participants	Role	Range of experience (Years)	Educational level		
			B.Sc	M.Sc	Ph.D.
4	Project manager	5-15	3	1	-
2	Consultant	10-20	-	1	1
4	Academic	5-9	-	-	4

Survey administration

The final version of the survey was distributed to 136 construction management experts in the UK, selected based on two criteria: (1) holding a professional role in the construction industry or academia related to construction education and (2) demonstrating proficiency in applying GenAI in construction projects. The respondent group included project managers, consultants, academics, and other project management professionals. Of the 136 experts surveyed, 101 responded, with a response rate of 74.3%. However, 21 responses were incomplete, leaving 80 valid responses for analysis. A more detailed discussion of the respondents' profiles is provided in the results and analysis section.

Stage Four: Development of a fuzzy-based risk quantification model

Fuzzy Set Theory (FST), introduced by Zadeh (1996), extends classical set theory by providing a framework for addressing uncertainty and imprecision in decision-making (Lauron et al., 2024; Gholamizadeh et al., 2022). Unlike traditional binary sets, FST allows for partial membership, making it particularly effective for representing and analysing linguistic variables such as "*very low*", "*low*", "*moderate*", "*high*", and "*very high*" (Akram et al., 2024). This flexibility enables the handling of vagueness and subjectivity inherent in human judgments (Mahmood et al., 2020; Chrysostom and Dwivedi 2016). Therefore, it appears clearly the key advantage of FST of the ability to formalise and quantify human knowledge by converting qualitative linguistic assessments into fuzzy numerical values, thus managing imprecise or incomplete information and reconciling conflicting expert opinions (Adak et al., 2024; Al-Mhdawi, 2023c). This makes it particularly valuable in scenarios where precise numerical data are unavailable or insufficient (Al-Mhdawi et al., 2024b). Given these strengths, FST was employed in this study to assess the significance of risks associated with integrating GenAI into RM of SCPs. Its capacity to accommodate ambiguity and incorporate expert judgment provided a systematic approach to quantifying risks, even in cases of uncertain or subjectively defined data. To operationalise this approach, a fuzzy-based model was developed for quantitatively assessing the significance of identified risks. The model utilised multiple input variables and a single output and was implemented using MATLAB R2024b (version 24.2). The following subsections outline the model's components and their role in the overall risk assessment process.

This research utilised six fuzzy controllers to assess risk significance. The first controller evaluated the IL of each risk based on its components: *ipc, ips, ipq, idm, and ior*. The second controller measured the probability of risk occurrence using *ea, aa*, and *otm*. While the third controller assessed the DL of each risk, incorporating *aa, acm,* and the output of the fourth controller, which determined the exposure level based on *rd* and *fo*. Finally, the fifth and main controller computed the overall risk significance by integrating the three primary assessment criteria (i.e., impact, probability, and detectability). Additionally, in each controller, the risk assessment criteria and their respective components were transformed into fuzzy sets using predefined membership functions. These fuzzy inputs were then processed within a fuzzy inference engine to estimate the level of each criterion and determine the overall significance of identified risks.

The architecture of the proposed GenAI risk assessment model is structured around three essential processes: fuzzification, fuzzy inference, and defuzzification. In the fuzzification process, both input and output variables were represented using triangular membership functions. This choice was guided by the functions' simplicity, computational efficiency, and effectiveness in capturing subjective and imprecise expert knowledge attributes that have made them widely adopted in similar fuzzy modelling applications (Gerla, 2013; Yager and Zadeh, 2012). For the inference stage, Mamdani's Fuzzy Inference System (MFIS) was employed due to its intuitive reasoning capabilities, ability to handle linguistic variables, and strong prevalence in engineering and decision-making literature (Mamdani and Assilian, 1975; Lootsma, 2010). Finally, the defuzzification process was carried out using the centroid of area method, which is commonly preferred in fuzzy systems for its accuracy in aggregating fuzzy sets into a single representative crisp output. This method is particularly useful in modelling expert judgments, as it balances multiple overlapping membership functions to produce a meaningful outcome (Kaynak et al., 2012). Collectively, these techniques form a cohesive framework suitable for modelling the uncertainty and subjectivity inherent in assessing the risks of integrating Generative AI into construction risk management.

To this end, a five-point Likert scale (ranging from Very Low (V.L) to Very High (V.H)) was used to define the inputs and outputs of the assessment model. Accordingly, five membership functions were established for the assessment components, criteria, and output variables. Figure 2 illustrated an example for the output risk significance memberships.

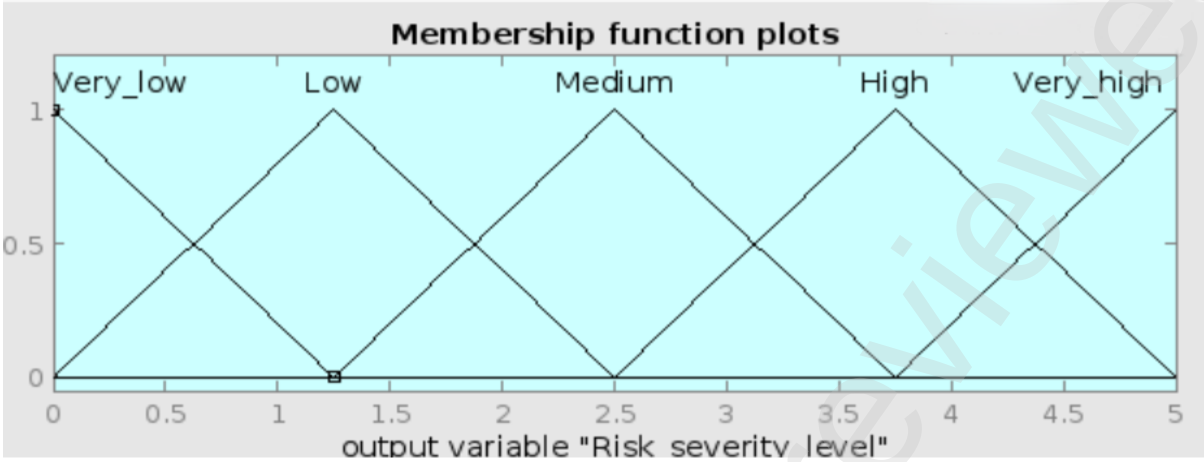

Figure 2. Membership functions for risk significance level

The fuzzy IF-THEN conditional statements were developed by adapting rule structures from previous fuzzy risk assessment models in construction (Dikmen et al., 2007; Al-Mhdawi et al., 2024a; Al-Mhdawi et al., 2022). These studies constructed fuzzy rule bases through systematic analysis of risk factors, linguistic categorization, and domain knowledge. Similarly, this study formulated the fuzzy rules by aligning with validated methodologies used for cost overrun risk assessment, oil and gas construction risk modelling, and emerging risk evaluation in construction, ensuring the model reflects best practices in fuzzy-based risk assessment.

A total of 550 rules were developed for the model, including 125 for impact on project insights, 25 for impact on the organisation, 125 for probability measurement, 25 for exposure level assessment, 125 for detectability, and 125 for overall risk significance. Examples of the developed IF-THEN rules for input variables (impact, probability, detectability) and their corresponding output (significance level) include: for the PL controller, Rule 14 states that if (*ea*) is very low, (*aa*) is medium, and (otm) is high, then PL is medium, while Rule 18 states that if (*ea*) is very low, (*aa*) is high, and (*otm*) is medium, then PL is medium; for the IL controller, Rule 70 states that if (*ipc*) is medium, (*ips*) is high, and (*ipq*) is very high, then IL is very high, and Rule 74 states that if (*ipc*) is medium, (*ips*) is very high, and (*ipq*) is very high, then IL is very high; for the DL controller, Rule 118 states that if (*ea*) is high, (*acm*) is very high, and (exposure) is medium, then DL is high, while Rule 122 states that if (*ea*) is very high, (*acm*) is very low, and (exposure) is high, then DL is low; and for the RL controller

(Risk Level), Rule 4 states that if (IL) is very low, (PL) is very low, and (DL) is low, then RL is medium, while Rule 8 states that if (IL) is very low, (PL) is low, and (DL) is medium, then RL is low. A sensitivity analysis was then conducted to evaluate the model's robustness and identify key risk drivers, following the approach proposed by Rathore et al. (2021). Key input variables were systematically varied by ±10%, and the corresponding changes in F-RN were monitored. The objective was to determine whether small variations in inputs would cause significant shifts in model outputs or rankings, thereby validating the model's stability. This approach aligned with the sensitivity analysis standards adopted in previous studies (Jain et al., 2016) and ensured that the model provided reliable insights for GenAI in RM for SCPs.

3. Results and Discussion

3.1 Risks identification and classification

The SLR identified 30 key risks associated with integrating GenAI into RM for SCPs. These risks were categorised into five main groups, namely: *Input quality risks*, *technological adaptability risks*, *ethical and governance risks*, *information integrity risks*, and *financial risks*, as outlined in Figure 3, along with their respective sources. The identification methods varied across studies, including GenAI model training and testing, case studies, interviews, questionnaire surveys, and focus group sessions (Mohamed et al., 2025a). In addition, research suggests that employing multiple methodologies to identify risks in construction projects is generally more effective than relying on a single approach, as it enhances the depth and reliability of findings (Sharma and Gupta, 2019). However, using a single method provides advantages such as simplicity, consistency, efficiency, and a more focused approach, facilitating detailed insights and improving replicability (Runeson, 2018). Despite these benefits, a single-method approach may introduce bias and the risk of overlooking critical factors, potentially limiting the comprehensiveness of risk identification. Therefore, integrating multiple identification methods is essential to ensure a robust and holistic assessment.

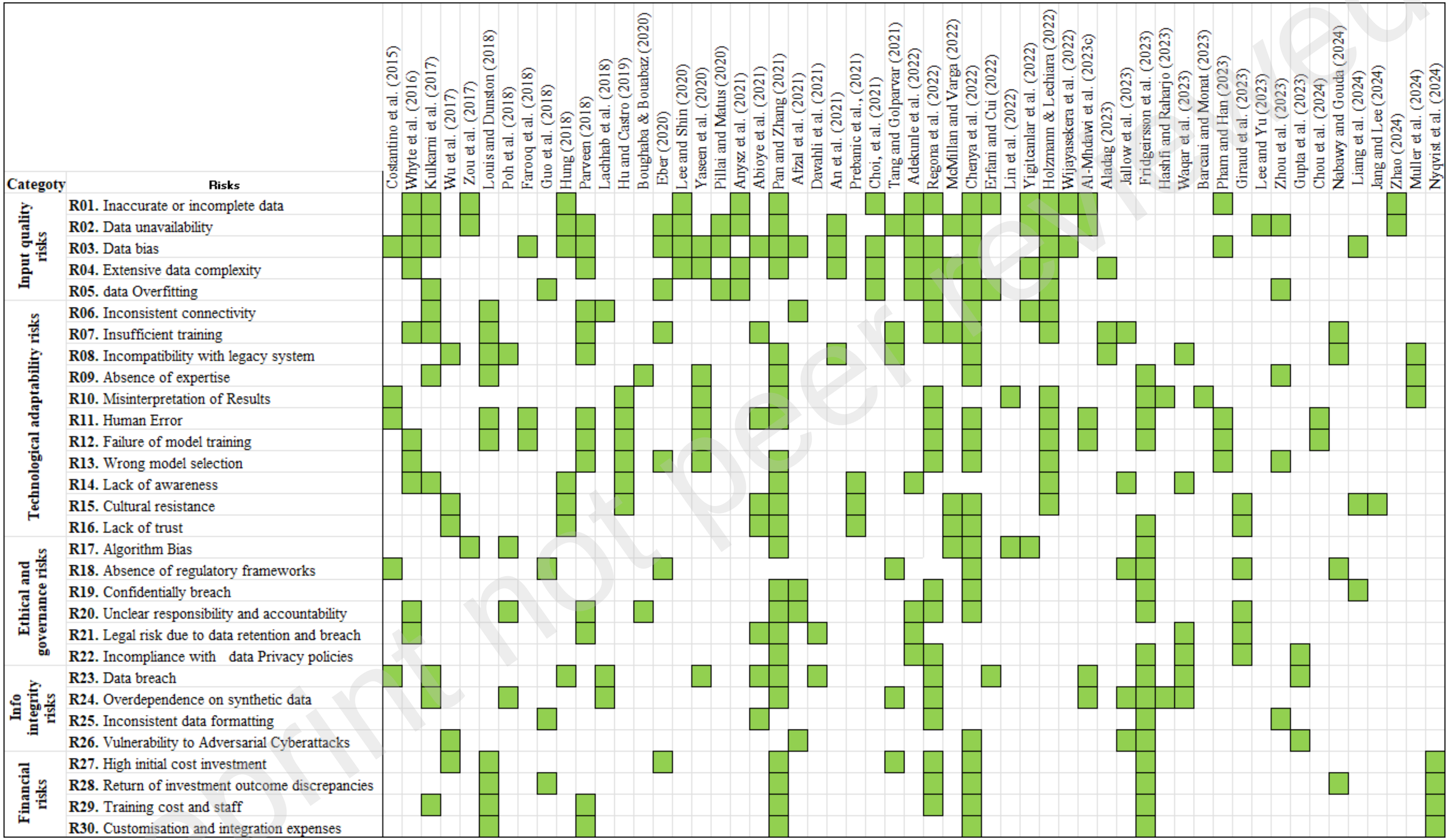

Figure 3. Mapping of identified GenAI-related risks across existing studies (2015–2025)

3.2 Profile of survey respondents

The survey respondents represented a range of roles within the construction industry, with the majority being Project Managers (62%), followed by other project management roles (23%), Academics (10%), and Consultants (5%). This distribution indicates a significant bias towards project management professionals, suggesting that most respondents were directly involved in supervising and managing construction projects. However, the relatively small proportion of consultants and academics may limit the diversity of perspectives, particularly in terms of expert advice and theoretical insights. In terms of professional experience, the respondents demonstrated a range of project management backgrounds. Most had between 1–5 years of experience (37%), followed by those with 6–15 years (32%) and 16–25 years (24%), whilst only a small portion reported having more than 25 years (6%). This indicates that the sample is predominantly composed of early to mid-career professionals, reflecting the views of those who are actively engaged in contemporary project management practices. The range of experience levels helps to provide a balanced understanding of challenges across different stages of professional development.

Educational qualifications among respondents were generally high, with 51% holding bachelor's degrees, 42% holding master's degrees, and 6% having completed doctorate degrees. This suggests that the majority of participants were well-educated, with a significant proportion possessing postgraduate qualifications. The strong educational background among the respondents enhances the reliability of the insights gathered, particularly in discussions related to advanced construction and risk management practices. Regarding familiarity with GenAI in construction management, the survey revealed varying levels of experience. The majority of participants identified themselves as having Intermediate experience (51%), followed by Beginner level (41%), and only a small group being classified as Experienced (9%). This distribution shows that whilst GenAI is gaining traction within the field, it remains relatively new, with most professionals still at the early or developing stages of adoption. These findings highlight opportunities for further training and capacity building to enhance the effective integration of GenAI into construction management practices. Figures 4–7 provide detailed illustrations of the respondents' profiles based on their roles, years of experience, educational qualifications, and experience levels with GenAI in construction management.

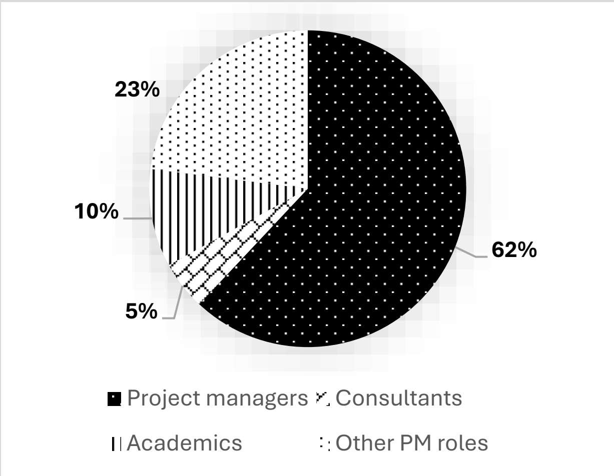

Figure 4. participants construction role

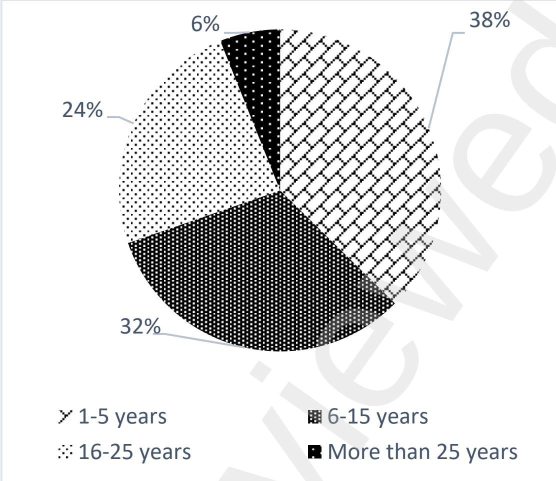

Figure 5. Years of experience

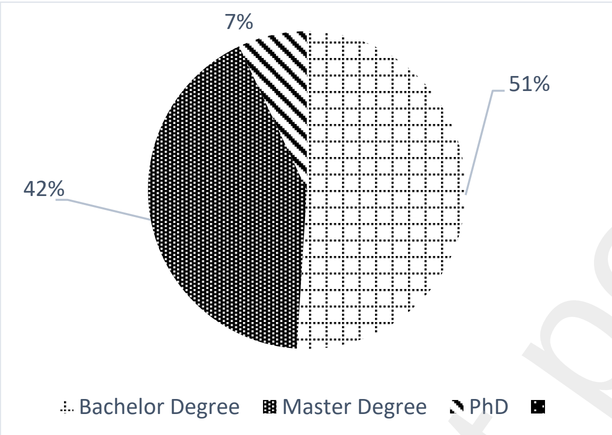

Figure 6. Education level

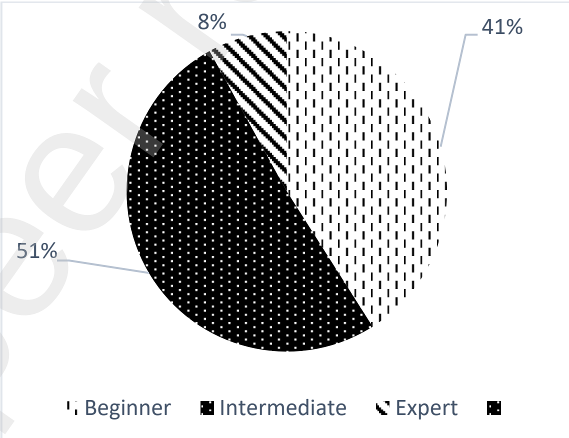

Figure 7. Level of experience with GenAI

3.3 *Architecture of the developed GenAI risk assessment model and its outputs*

As described in stage three of the research methodology, the proposed risk assessment model was designed using six fuzzy controllers via MATLAB R2024b, with each controller dedicated to evaluating a specific risk dimension. The first controller assessed the impact on project insights, using three input variables: *ipc, ips,* and *ipq*. The second controller evaluated the impact on the organisation, incorporating *idm* and *ior*, the summation of the outputs of first and second controller represented the overall IL. Moreover, the third controller measured the probability of risk occurrence, with inputs *ae, aa,* and *otm*, producing the PL as the output. The fourth controller assessed the DL, utilising *ae*, *acm*, and the output from the fifth controller, which measured exposure level based on *fo* and *rd*. Finally, the sixth controller integrated the outputs of the IL, PL, and DL, generating the overall risk significance level for integrating GenAI into RM for SCPs. This structured approach ensured a comprehensive and systematic evaluation of risk factors, enabling a more robust and data-driven assessment of potential risks.

The fuzzy controllers were designed using the IF-THEN rules presented in stage four of methodology, while Figure 8 illustrates the architecture of the proposed risk assessment model. To visualise the relationships between fuzzy controllers' input and output variables, three-dimensional mappings were generated using the Fuzzy Logic Surface Viewer. These graphical representations illustrate how the output variables vary in response to changes in the input variables, enhancing interpretability. Furthermore, Figures 9–14 depict the dependencies for each controller, where each surface plot includes two input variables and one output variable—specifically, for impact, probability, detectability, exposure, and overall significance level. For instance, Figure 14 illustrates the risk significance surface based on total impact and probability. the risk significance level is represented by colour intensity, with higher risk significance corresponding to more intense colour gradients. These visualisations provide a clear and intuitive understanding of the interactions between risk factors, supporting a more informed risk assessment process.

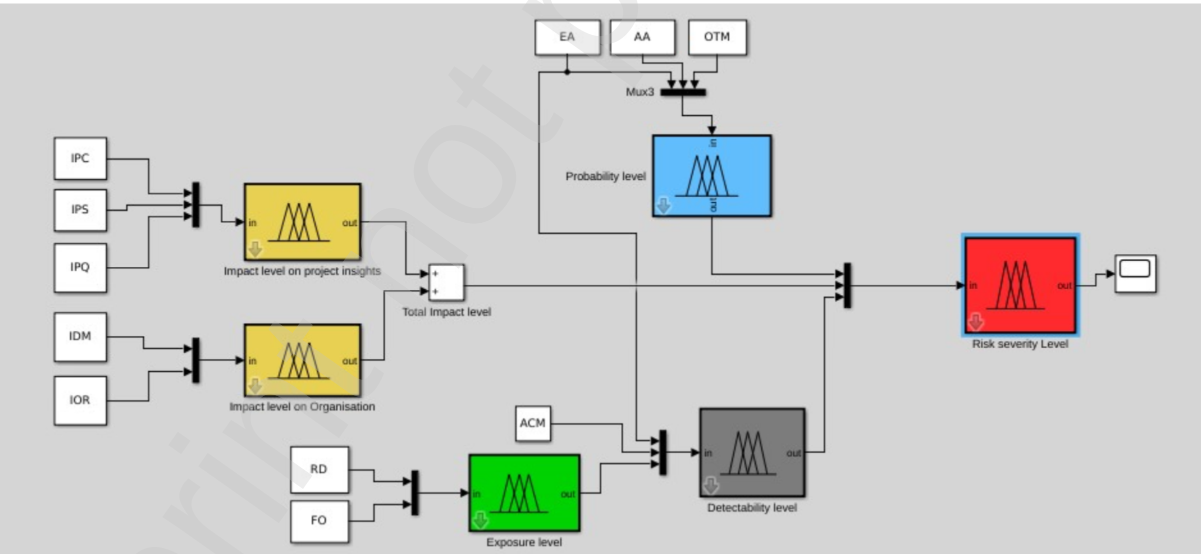

Figure 8. The proposed risk assessment model

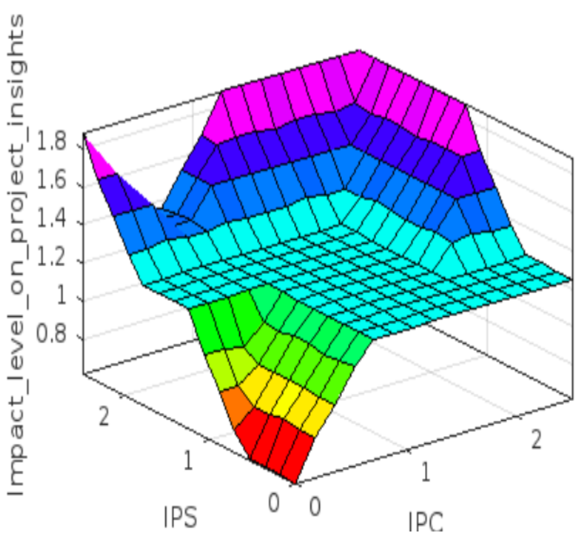

Figure 9. Impact level on project insights

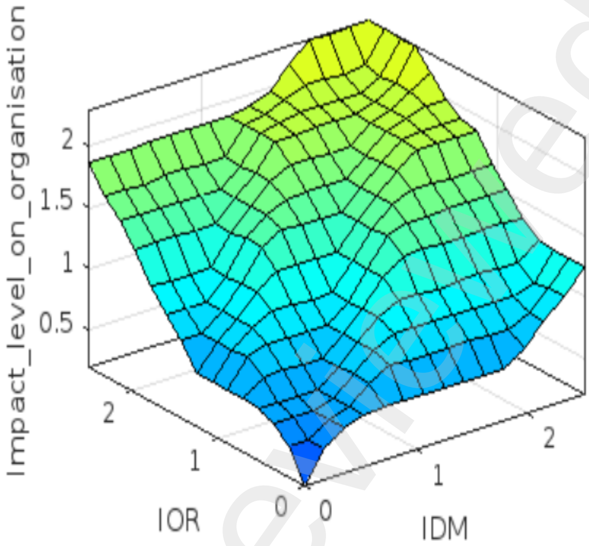

Figure 10. Impact level on organisation

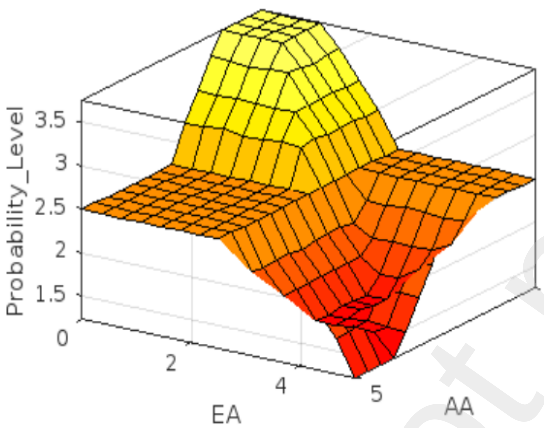

Figure 11. Probability level surface plot

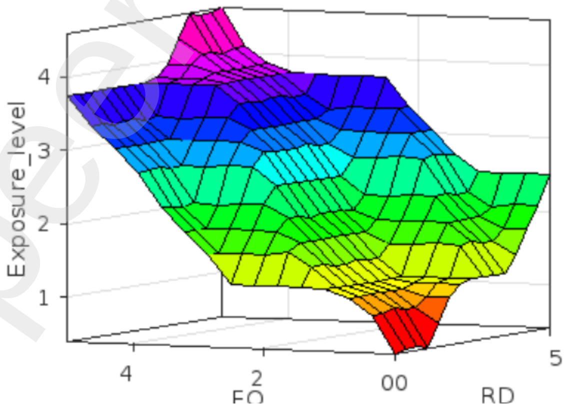

Figure 12. Exposure level surface plot

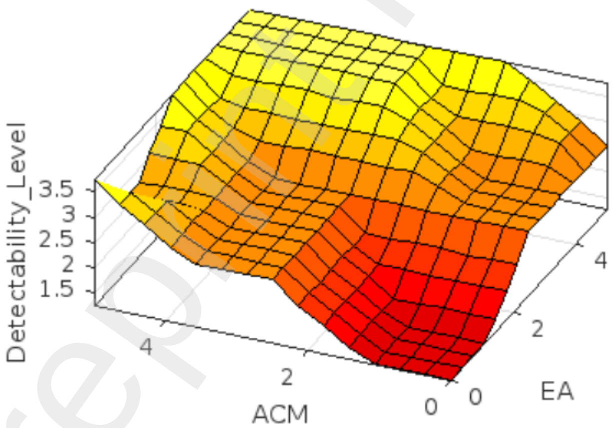

Figure 13. Detectability level surface plot

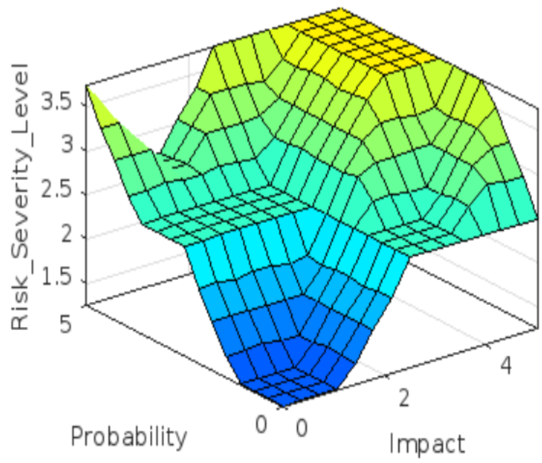

Figure 14. Risk significance level surface plot

To this end, the mean values of *ipc, ips, ipq, idm, ior, ae, aa, otm, acm, fo,* and *rd* were used as crisp inputs, as presented in columns 2 to 13 of Table 4. These values were then processed through the following steps: (1) Fuzzification using triangular membership functions, (2) Inference processing through IF-THEN rules, (3) Control mechanism using a Mamdani-type inference system and defuzzification using the centre of area method. Ultimately, the risk significance level of each risk factor associated with integrating GenAI into RM for SCPs was computed, represented as F-RN, along with its ranking, as shown in columns 14 and 15 of Table 2.

Table 2. Fuzzy analysis

Category	Risk ID	Probability Level (Mean Values)			Impact level (Mean values)					Detecting level (Mean values)		Exposure level (Mean values)		(F-RN)	Category rank	Overall rank
		ea	aa	otm	ipc	ips	ipq	idm	ior	ea	acm	rd	fo			
Input quality risks	R01	3.52	3.43	3.36	3.9	3.82	3.74	3.86	3.75	3.52	3.59	3.46	3.3	3.52	3	8
	R02	3.6	3.51	3.33	3.91	4	3.82	4.04	3.72	3.6	3.52	3.47	3.18	3.63	1	2
	R03	3.59	3.42	3.18	3.44	3.43	3.62	3.75	3.53	3.59	3.43	3.34	3.17	3.59	2	4
	R04	3.37	3.36	3.35	3.42	3.5	3.37	3.44	3.11	3.37	3.37	3.34	3.22	3.37	5	21
	R05	3.4	3.27	3.3	3.46	3.47	3.48	3.48	3.35	3.4	3.43	3.23	3.01	3.4	4	18
Technological adaptability risks	R06	3.34	3.27	3.23	3.31	3.45	3.49	3.34	3.29	3.34	3.28	3.06	3	3.34	8	22
	R07	3.59	3.24	3.34	3.54	3.55	3.58	3.64	3.47	3.59	3.4	3.4	3.19	3.61	2	3
	R08	3.25	3.25	3.16	3.49	3.48	3.47	3.42	3.31	3.25	3.29	3.24	3.05	3.25	9	25
	R09	3.51	3.27	3.34	3.86	3.75	3.67	3.62	3.69	3.51	3.45	3.26	3.07	3.51	4	9
	R10	3.49	3.39	3.31	3.81	3.77	3.68	3.84	3.79	3.49	3.41	3.32	3.19	3.49	5	10
	R11	3.64	3.53	3.4	3.75	3.65	3.71	3.61	3.64	3.64	3.67	3.28	3.33	3.64	1	1
	R12	3.25	3.23	3.27	3.55	3.63	3.59	3.56	3.47	3.25	3.44	3.19	3.08	3.24	10	26
	R13	3.42	3.47	3.4	3.78	3.64	3.21	3.53	3.67	3.42	3.39	3.31	2.93	3.42	6	15
	R14	3.56	3.44	3.36	3.51	3.49	3.57	3.37	3.45	3.56	3.31	3.08	2.96	3.56	3	6
	R15	3.23	3.14	3.22	3.04	3.12	3.16	3.28	3.23	3.23	3.23	3.16	3.08	3.23	11	27
	R16	3.38	3.24	3.29	3.03	3.18	3.05	3.44	3.35	3.38	3.19	3.22	3.16	3.38	7	20
Ethical and governance risks	R17	3.29	3.27	3.14	3.3	3.24	3.29	3.48	3.32	3.29	3.5	3.36	3.11	3.29	4	24
	R18	3.41	3.45	3.11	3.51	3.4	3.34	3.47	3.48	3.41	3.43	3.35	2.96	3.41	3	16
	R19	3.45	3.48	3.45	3.4	3.44	3.11	3.55	3.92	3.45	3.29	3.52	3.16	3.45	2	12
	R20	3.55	3.39	3.26	3.51	3.55	3.48	3.5	3.56	3.55	3.34	3.31	3.09	3.55	1	7
	R21	3.41	3.39	3.18	3.71	3.5	3.47	3.31	3.87	3.41	3.44	3.23	3.05	3.41	3	16
	R22	3.45	3.27	3.36	3.36	3.38	3.35	3.23	3.59	3.45	3.19	3.04	3.04	3.45	2	12
Information integrity risks	R23	3.59	3.41	3.03	3.68	3.47	3.34	3.46	4.03	3.59	3.58	3.24	3.04	3.59	1	4
	R24	3.41	3.35	3.33	3.37	3.22	3.2	3.27	3.13	3.41	3.26	3.33	3.07	3.39	3	19
	R25	3.42	3.45	3.21	3.44	3.4	3.11	3.41	3.38	3.42	3.56	3.15	3.09	3.44	2	14

	R26	3.39	3.36	3.42	3.6	3.43	3.22	3.41	3.75	3.39	3.43	3.27	3.14	3.33	4	23
Financial risks	**R27**	3.43	3.38	3.23	3.81	3.18	3.12	3.22	3.33	3.43	3.26	3.36	3	3.21	2	28
	R28	3.47	3.53	3.44	3.5	3.11	3.14	3.3	3.49	3.47	3.18	3.17	2.89	3.47	1	11
	R29	3.38	3.26	3.21	3.58	3.04	3.12	3.15	3.19	3.38	3.37	3.13	2.93	3.11	4	30
	R30	3.31	3.44	3.29	3.41	3.27	3.22	3.06	3.14	3.31	3.33	3.23	3.05	3.17	3	29

3.4 Sensitivity analysis

To evaluate the robustness of the fuzzy risk assessment model, a sensitivity analysis was conducted following the approach outlined in the methodology. Each input parameter was varied by ±10%, and the resulting changes in the risk significance scores (F-RN) were observed. The analysis showed that the variation in F-RN values remained within a ±6% to ±6.5% range across the top risk categories, indicating strong model stability. Importantly, these variations did not alter the relative ranking of the risks. Figure 15 present changing one of the inputs to the F-RN.

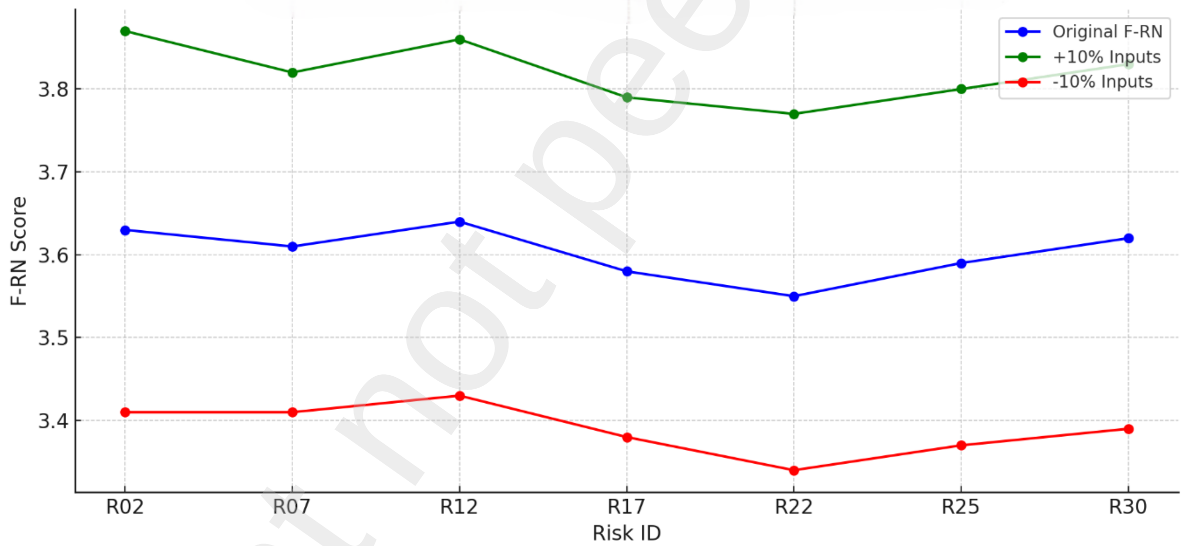

Figure 15. Sensitivity Analysis of Fuzzy Risk Scores under ±10% Input Variations

3.5 Discussion of Research Findings

This section discusses the top risk categories associated with the integration of GenAI into RM for SCPs, based on the findings of the developed assessment model. As outlined in the preceding stages of the research methodology, these risks in each category were evaluated for their significance levels, enabling the identification of the most critical areas.

Input quality-related risks

Input quality risks encompass factors related to the accuracy, completeness, consistency, and contextual relevance of data used in training and deploying GenAI models (Chenya et al., 2022; Holzmann and Lechiara, 2022). These risks are particularly salient in Sustainable Construction Projects (SCPs), where GenAI-enabled RM relies heavily on clean, diverse, and current datasets to generate reliable predictions and inform effective decision-making (Wijayasekera et al., 2022). Findings from the fuzzy analysis highlight the criticality of input quality risks. Specifically, R02 (data unavailability) was ranked 2nd overall (F-RN: 3.63), R03 (data bias) ranked 4th (F-RN: 3.59), and R01 (inaccurate or incomplete data) ranked 8th (F-RN: 3.52). These high rankings clearly demonstrate that substandard data inputs can severely undermine the predictive validity and reliability of GenAI models used in SCP risk assessments.

The effective deployment of GenAI in SCPs hinges critically on the quality and availability of input data, where inaccuracies, omissions, or biases can significantly compromise the integrity of risk identification and mitigation strategies (Aldoseri et al., 2023). Data unavailability—often due to fragmented data silos or inaccessible historical records—restricts GenAI's ability to learn from past risk occurrences, thereby limiting its capacity to generalize effectively and produce reliable forecasts for future project scenarios (Chen and Chen, 2024). Similarly, data bias introduces systematic distortions in model outputs, potentially misclassifying emerging threats or ignoring contextual factors unique to SCPs, such as regulatory, environmental, or stakeholder-driven complexities (Chenais et al., 2022).

Inaccurate or incomplete data further compounds the challenge by introducing noise, uncertainty, and missing contextual signals. These deficiencies not only degrade model performance but also jeopardize decision outcomes across project planning, risk assessment, and stakeholder communication (Kumar et al., 2024; Delello et al., 2025). Erroneous data points or poorly annotated training samples can lead to biased parameter estimation, flawed mitigation strategies, and ineffective prioritization of risks. As Zhang and Zhang (2023) note, poor data annotation practices significantly reduce AI system reliability, especially in dynamic and risk-sensitive environments such as SCPs. Moreover, the implications of data quality issues extend beyond technical performance. As Steimers and Schneider (2022) highlight, data governance also encompasses ethical and operational dimensions, especially in SCPs where RM decisions often have long-term sustainability implications—including financial losses, safety breaches, or environmental degradation. Addressing these challenges demands a multi-pronged strategy involving stringent data validation protocols, robust data governance frameworks, and cross-stakeholder collaboration to enable seamless data sharing and integration (Ambasht, 2023; Adesina, Iyelolu and Paul, 2024).

Technological adaptability-related risks

Technological adaptability risks refer to the challenges involved in embedding GenAI into existing construction management workflows, systems, and decision-making processes. These risks are especially significant in the construction industry, where human judgment, domain expertise, and contextual interpretation remain indispensable to project delivery (Hu & Castro, 2019; Adekunle et al., 2022; Chowdhury et al., 2024). Fuzzy analysis highlights human error (R11) as the most critical risk in this category, ranking 1st overall with an F-RN of 3.68. This underscores a key vulnerability: while GenAI can produce sophisticated and valuable insights, its effectiveness is ultimately constrained by the competence and attentiveness of the human actors interpreting and applying those outputs (Grewal et al., 2024). This finding highlights the critical importance of the human–machine interface in construction workflows, where the quality of decision-making is only as strong as the human ability to engage meaningfully with GenAI systems, as emphasized by Epstein et al. (2023), Ghimire et al. (2023), and Hilgard et al. (2019).

The second most significant risk in this category is insufficient training (R07), which ranks 3rd overall (F-RN: 3.60). This reflects a pervasive lack of readiness among construction professionals to effectively utilize and collaborate with GenAI technologies, leading to potential inefficiencies, poor system adoption, and suboptimal integration outcomes (Taiwo et al., 2024). Inadequate exposure to digital tools or unfamiliarity with GenAI functionality can result in dependency without understanding, weakening confidence in AI-assisted decisions and increasing the likelihood of operational errors. Closely related is the risk of misinterpretation of GenAI results (R10), which ranks 10th overall (F-RN: 3.46). Limited GenAI literacy can precipitate misguided conclusions, particularly when outputs are taken at face value without a thorough understanding of underlying assumptions, model limitations, or contextual nuances (Grewal et al., 2024; Hassoun et al., 2024). These misjudgments can undermine project outcomes and erode stakeholder trust, especially when decisions based on flawed interpretations lead to delays, cost overruns, or misaligned risk responses.

These findings are echoed in broader literature emphasizing the need for not only technical training but also the cultivation of higher-order cognitive skills. Construction professionals must be equipped not just to operate GenAI tools, but also to critically evaluate, contextualize, and apply GenAI-derived insights within complex, dynamic project environments (Pan & Zhang, 2021; Lee & Shin, 2020). This requires the development of GenAI-focused curricula and comprehensive training programs that bridge the gap between algorithmic output and practical project requirements. Proactively managing these technological adaptability risks is essential for unlocking the full potential of GenAI in construction. It calls for a multidimensional strategy that includes continuous workforce upskilling, intuitive system design, and strong digital leadership to reduce friction and resistance (Ghimire et al., 2023). Such efforts foster innovation while minimizing the risk of errors and misapplications that could otherwise undermine project success (Reis & Melão, 2023).

Ethical and governance-related risks

Ethical and governance risks encompass the legal, regulatory, and ethical challenges arising from the deployment of GenAI in SCPs. These risks are particularly significant in data-sensitive, high-stakes environments where decisions influenced by AI may have far-reaching consequences (Rane, 2023; Regona et al., 2024). As GenAI technologies become more integrated into project decision-making, questions of fairness, transparency, and accountability become increasingly pressing. Based on the fuzzy analysis, the most critical risk in this category is unclear responsibility and accountability (R20), which ranks 1st within the category and 7th overall with an F-RN of 3.55. This highlights a major concern in GenAI-assisted decision-making: determining who is liable when AI-generated insights contribute to negative project outcomes (Evans et al., 2022). As construction projects become more digitized and AI-reliant, ambiguity in accountability can create legal grey areas—particularly in hybrid decision-making settings where responsibilities are shared between human actors and AI systems (Hendrycks et al., 2023).

Building on this concern, confidentiality breaches (R19) and noncompliance with organisational data privacy policies (R22) are also ranked prominently—tied at 2nd within the category and 12th overall (F-RN: 3.45). These risks reflect heightened anxieties about the misuse of sensitive data, unauthorized access, and the potential exposure of confidential project information. The reliance of GenAI models on large and often sensitive datasets exacerbates these concerns, making data protection a central issue (Stahl, 2021; Palaniappan et al., 2024). Beyond the risk of regulatory penalties, such breaches can significantly damage the reputational standing of construction firms, particularly those involved in publicly funded or regulated SCPs (Ghimire et al., 2024). Closely related are the risks associated with non-transparent decision-making processes, namely R18 and R21, both of which rank 3rd in the category and 16th overall with an F-RN of 3.41. These risks highlight the intrinsic opacity of many GenAI systems—especially deep learning models—that often function as "black boxes," where the internal logic driving decisions is not easily understandable to users. This lack of explainability can diminish trust, hinder stakeholder engagement, and limit the practical adoption of GenAI in critical project functions (Compton et al., 2024; Kandasamy, 2024).

Together, these findings reinforce the broader call in the literature for the development of robust legal, ethical, and governance frameworks tailored to the unique context of GenAI in the built environment (Parveen, 2018; Pillai and Matus, 2020; Regona et al., 2022). The absence of clearly delineated roles, enforceable standards, and transparent auditing mechanisms presents a substantial barrier to responsible GenAI deployment. Legal uncertainty over liability, combined with ethical challenges surrounding data use and algorithmic fairness, necessitates proactive governance approaches capable of managing these evolving risks. Integrating ethical and regulatory considerations into GenAI adoption strategies therefore demands more than baseline compliance (Zhang and Zhang, 2023; Raza et al., 2025). It requires the establishment of clear accountability structures, alignment with data governance policies, and the embedding of responsible AI practices into construction project workflows (Xue and Pang, 2022). These efforts are essential for building stakeholder confidence and ensuring that GenAI contributes meaningfully and sustainably to risk management in SCPs.

Information integrity-related risks

Information integrity risks encompass threats related to data security, authenticity, and system reliability in GenAI-powered RM. As construction firms increasingly digitise workflows and integrate AI-driven tools, maintaining the integrity of the information supporting these systems becomes essential (Rane, 2023). These risks are particularly pertinent in SCPs, where risk assessments often rely on complex, multi-source data environments. The broader literature emphasises that vulnerabilities in data handling not only undermine trust in AI systems but also increase the likelihood of flawed project decisions, cost escalations, and reputational damage (Gupta et al., 2023; Sai et al., 2024).

The fuzzy analysis identifies data breach (R23) as the most critical risk in this category, ranking 1st within the group and 4th overall with an F-RN of 3.59. This finding aligns with prior research that highlights cybersecurity as a foundational challenge in AI integration, particularly in sectors handling sensitive, high-value data (Jada and Mayayise, 2023). In construction, where data-sharing across partners, contractors, and regulatory bodies is routine, the threat of unauthorized access or malicious exploitation is significantly amplified. Compounding this concern, earlier studies have noted the lack of sector-specific cybersecurity protocols as a key barrier to the safe deployment of AI in construction (Ghimire et al., 2024), reinforcing the urgency of addressing this risk.

The second-highest risk in this category is data fabrication or manipulation (R25), which ranks 14th overall with an F-RN of 3.44. This concern is well-documented in the AI ethics literature, where tampered or falsified data is known to compromise model outputs by introducing bias or misleading patterns (Kandasamy, 2024; Raza et al., 2025). In the context of SCPs—where project conditions are often dynamic, localised, and non-standardised—unverified or manipulated data can distort GenAI's ability to accurately assess risk exposures. These results echo previous calls for implementing data provenance systems and real-time validation mechanisms as critical safeguards in GenAI-driven decision environments (Compton et al., 2024). The third major concern is overdependence on synthetic data (R24), which ranks 19th overall with an F-RN of 3.39. While synthetic data offers scalability and addresses data privacy constraints, it may fall short in capturing the complexity, variability, and contextual nuances inherent in real-world construction projects (Breugel and Schaar, 2023). Prior studies have cautioned that an excessive reliance on synthetic datasets may result in blind spots during risk prediction, especially in industries like construction where workflows are heterogeneous and non-standardised (Stahl, 2021; Sandhaus et al., 2024).

Together, these findings reinforce a growing body of literature advocating for comprehensive strategies to ensure information integrity in GenAI implementation. This includes the development of robust cybersecurity infrastructure, data authenticity protocols, and balanced data sourcing practices (Jallan and Ashuri, 2020; Regona et al., 2022; Yao and Soto, 2024). Cybersecurity must go beyond basic protections to encompass AI-specific safeguards such as encrypted model pipelines and context-sensitive intrusion detection systems (Singh and Joshi, 2024). Simultaneously, ensuring data authenticity through validation tools, audit trails, and provenance tracking is essential to prevent flawed or manipulated inputs from undermining trust in AI-generated outputs. Moreover, the risks associated with synthetic data highlight the need for thoughtful integration of real-world data to maintain model reliability. While synthetic data can supplement scarce datasets, it should not substitute the richness and unpredictability of actual project conditions (Marwala et al., 2023). Without these safeguards in place, the use of GenAI in RM remains susceptible to both technical failures and ethical breaches, which can significantly erode stakeholder trust and jeopardise project success (Barrett et al., 2023; Stanovsky et al., 2025). Ultimately, aligning technical measures with construction-specific standards and ethical guidelines is vital to ensure responsible and effective GenAI integration in risk management.

Financial-related risks

Financial risks represent the economic uncertainties and cost-related concerns tied to the adoption and integration of GenAI technologies into risk management practices for SCPs. These risks are especially significant in a sector where project budgets are tightly managed and investments in emerging technologies are often scrutinized for their long-term value (Regona et al., 2024; Salzano et al., 2024). In such settings, the perceived financial viability of GenAI becomes a key factor influencing its acceptance among construction stakeholders (Ghimire, Kim, and Acharya, 2024), particularly when the return on investment (ROI) is not immediately evident.

In this study, the fuzzy analysis identified ROI outcome discrepancies (R28) as the most critical risk within the financial category. It ranked 1st in this domain and 11th overall, with an F-RN of 3.47. This finding underscores the prevalent uncertainty regarding the actual value GenAI may deliver over time (Masood, 2025). While GenAI has the potential to enhance decision-making accuracy, reduce exposure to risk, and streamline operational processes, many project managers remain cautious (Sai et al., 2025). A major contributor to this caution is the gap between the anticipated benefits and the realized outcomes, which discourages resource allocation in the absence of reliable financial forecasting and ROI evaluation tools (Fabricius and Büttgen, 2015).

Following closely is the risk of high initial investment cost (R27), ranked 2nd in the financial category and 28th overall, with an F-RN of 3.21. Although high implementation costs are often seen as a barrier to digital innovation, the relatively lower overall ranking suggests that stakeholders might be open to absorbing these upfront costs—provided there is a well-defined path to long-term value. However, the magnitude of investment required for GenAI infrastructure, licensing, workforce training, and integration poses a substantial challenge, especially for small to medium-sized firms with limited financial flexibility and digital maturity (Gurjar et al., 2024). The third-highest risk in this category, customization and integration expenses (R30), ranks 3rd within the financial domain and 29th overall, with an F-RN of 3.17. This risk highlights the financial burden associated with tailoring GenAI tools to specific project or organizational needs. Ensuring system compatibility, modifying workflows, and training personnel all incur additional costs (Ghimire, Kim, and Acharya, 2024). These often hidden or underestimated expenses can further complicate investment planning and hinder the scalability of GenAI implementation, particularly in resource-constrained construction environments.

These findings are consistent with prior studies that underline the importance of strategic financial planning when introducing advanced digital technologies into traditional project environments. As Liddell (2025), Tajuddin (2025), and Xu and Cho (2025) argue, the lack of structured cost–benefit frameworks and performance-tracking mechanisms can obscure the financial justification for GenAI investment. Developing transparent ROI assessment tools, aligning GenAI adoption with broader business objectives, and setting realistic performance expectations are necessary steps to ensure financially sound and sustainable implementation in SCP risk management contexts.

4. Conclusion

This research presents a novel risk assessment model designed to evaluate the significance level of risks associated with integrating GenAI into RM for SCPs. The study aimed to (1) identify and categorise key risk factors related to GenAI integration and (2) quantify their significance level based on probability of occurrence, impact on project objectives, and DL. To achieve these objectives, a structured multi-stage methodology was adopted. Initially, a SLR was conducted, analysing 55 high-quality articles selected based on rigorous inclusion and exclusion criteria. Following this, a multi-criteria risk assessment model, grounded in FST, was developed to systematically evaluate these risks, incorporating expert insights to enhance accuracy and reliability. The subsequent stage involved a survey of 80 construction professionals, who assessed the identified risks across three key dimensions: probability, impact, and detectability. Each dimension was evaluated in detail using criteria established through a group session with five construction risk management experts. Finally, the risks were analysed using the proposed model and validated through a follow-up focus group session with industry experts, ensuring both accuracy and practical relevance. The research identified 30 distinct risks, classified into five overarching categories, as summarised in Table 3.

Among the identified risks, three emerged as the most significant challenges to GenAI integration: (1) human error, (2) data unavailability, and (3) insufficient training. The findings highlight that GenAI's effectiveness is highly dependent on human expertise and the reliability of data, with errors in interpretation and application posing substantial risks. Data unavailability remains a critical barrier, as inconsistent or incomplete datasets can undermine AI-driven decision-making. Additionally, insufficient training limits the industry's ability to implement and manage GenAI effectively. To ensure successful adoption, it is essential to enhance data accessibility, invest in structured GenAI training, and develop strategies to mitigate human error. Without these measures, the industry's ability to leverage GenAI at scale remains uncertain, restricting its transformative potential.

4.1 Theoretical and practical implications

This study provides both theoretical and practical contributions to construction risk management by introducing a novel risk assessment model tailored to evaluate the significance level of risks associated with GenAI integration. Theoretically, it advances the understanding of GenAI-driven risk management by systematically identifying and categorising key risk factors through SLR. This framework can serve as a foundation for future theoretical research and provide a structured approach for prioritising critical risks, guiding further studies on mitigation strategies. Additionally, the quantification of risks offers insights into their relative significant, enabling researchers to explore targeted solutions for high-impact risks.

Practically, the proposed model provides construction professionals with a structured framework to assess, prioritise, and mitigate GenAI-related risks. By addressing these risks, organisations can refine their AI adoption strategies, enhance decision-making processes, and reduce project uncertainties. Furthermore, the model can serve as a decision-support tool, aiding industry stakeholders in proactively managing risks associated with GenAI integration. Ultimately, this research strengthens the industry's readiness for AI-driven transformation, ensuring its responsible and effective implementation in construction risk management.

4.2 Research limitation

Despite its valuable contributions, this study has several limitations. First, while the research incorporates expert judgment through questionnaire surveys, it should be noted that although 30% of the participants had over 16 years of experience in construction management, only 9% were classified as advanced users of GenAI in RM of SCPs. This may have impacted the depth of insights into the integration of GenAI in construction risk management, and the results could have differed had more experts with advanced experience in GenAI applications been included. Secondly, the study primarily focused on experts from the UK, which may limit the generalizability of the findings to the broader international construction industry. Different countries may face unique challenges related to GenAI integration, especially in the context of financial risks. For instance, countries with limited resources or funding might perceive financial risks as more severe than those with more developed infrastructures and budgets. Therefore, including experts from a variety of international settings could offer a more comprehensive understanding of the global implications of integrating GenAI into RM for SCPs and highlight potential regional differences in risk perceptions and priorities.

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