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Quantifying the Risks of Generative AI Integration in Construction Risk Management: A Fuzzy Logic Perspective

Mohamed Abdelwahab Hassan Mohamed[1], M.K.S. Al-Mhdawi[2,3]
[1]York Business School, York St John University, York, UK
[2]School of Computing, Engineering and Digital Technologies, Teesside University, Middlesbrough, UK
[3]Department of Civil, Structural, and Environmental Engineering, Trinity College Dublin, Dublin, Ireland

Email: m.mohamed@yorksj.ac.uk, almhdawm@tcd.ie

ABSTRACT: This study investigates the socio-technical risks associated with integrating Generative Artificial Intelligence (GenAI) into Construction Risk Management (CRM). A three-stage methodology was adopted. First, a structured systematic literature review was conducted using Scopus to identify socio-technical risks through database and journal identification, keyword-based screening, and conventional content analysis. Second, a questionnaire survey was developed and administered to 136 construction management experts in the UK to evaluate the significance of the identified risks. Third, a fuzzy set theory-based risk quantification model was developed and implemented in MATLAB to handle uncertainty in expert judgment and to compute an overall fuzzy risk number for ranking. Twelve socio-technical risks were analysed, representing human capability, adoption dynamics, and governance and security concerns. The results indicate that insufficient training and data breaches are the highest priority risks, followed by a lack of awareness and unclear responsibility and accountability. The study provides actionable insights for practitioners and policymakers by supporting targeted mitigation strategies focused on workforce readiness, data governance, and accountable decision structures, thereby enabling responsible GenAI integration in CRM.

KEY WORDS: Generative Artificial Intelligence; Risk Management; Sustainable construction; Fuzzy Set Theory

1 INTRODUCTION

The rapid advancement of Generative Artificial Intelligence (GenAI) is creating new opportunities for the construction sector, particularly in data intensive and time pressured decision environments [1]. In construction risk management (CRM), GenAI can support faster risk identification, improve the coverage of risk registers, and enhance decision quality through transforming large volumes of project information into actionable insights [2]. These capabilities are increasingly relevant to modern projects where delivery involves tight programmes, complex supply chains, and diverse stakeholder expectations, all of which intensify risk exposure and increase the need for timely and defensible risk responses [3].

However, the integration of GenAI into CRM is not only a technical change. It is a socio-technical shift that reshapes how people work, how decisions are justified, and how accountability is assigned. Socio-technical risks emerge from the interaction between GenAI outputs, human judgement, organisational culture, and governance constraints [4]. They include workforce capability risks such as inadequate training, limited expertise, and misinterpretation of outputs, alongside trust and adoption risks that influence whether GenAI is used consistently and responsibly [5]. They also include governance and societal risks linked to confidentiality, privacy compliance, accountability ambiguity, and security exposure, which can undermine stakeholder confidence and generate legal or reputational consequences. These risks can reduce the reliability of risk assessments, create disputes over responsibility, and ultimately contribute to schedule delay, cost escalation, and weakened stakeholder satisfaction [6].

Although, the wider construction literature increasingly highlights the benefits of GenAI enabled decision support, the risk evidence base remains fragmented and is often discussed under broader AI adoption narratives rather than GenAI specific realities [7]. Much prior work addresses general AI in construction or examines isolated issues such as data or ethics, without a focused of socio-technical risks that are most relevant to GenAI integration in CRM. As a result, decision makers lack a structured understanding of which socio-technical risks are most significant, how they compare in severity, and where practical controls should be prioritised during adoption [7],[8],[9].

This paper addresses this gap via identifying and categorising the key socio-technical risks associated with integrating GenAI into CRM and evaluating their relative significance to support prioritisation. The findings contribute to the growing body of knowledge on risk management in technologically advanced construction settings and provide actionable insights to help organisations adopt GenAI responsibly while protecting decision quality, governance integrity, and stakeholder trust.

2 METHODOLOGY

A three-stage, multi-method approach was adopted to support data collection, analysis, and processing. The application of a multi-method research design offers clear advantages, as it enhances both the depth and breadth of analysis [10], [11]. As illustrated in Figure 1, this methodological diversity captures the complexity of the subject matter while providing a comprehensive and coherent framework for data interpretation [12].

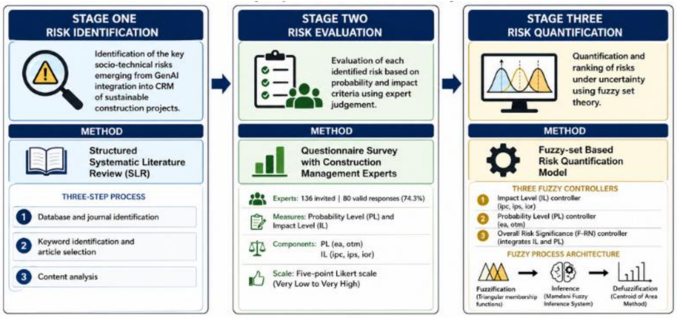

Figure 1. Adopted research methodology

2.1 *Stage one: risk identification*

This stage adopts a structured, three-step methodology for literature collection and analysis, designed to thoroughly examine existing studies and identify the key Socio-technical risks associated with integrating GenAI into CRM. 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.

2.1.1 Step one 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.

2.1.2 Step two 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 technical risks*", "*GenAI in RM*", and "*GenAI in 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 include a wide range of studies addressing the challenges and applications of GenAI in CRM 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 construction sector.

2.1.3 Step three content analysis

This study adopted the conventional approach, a data-driven, open-ended method that allows identified risks to emerge organically without the constraints of predefined frameworks. This approach, suitable for both qualitative and quantitative analysis, and particularly well-suited for investigating the emerging integration of GenAI into CRM, as it facilitates the extraction of detailed themes directly from the data [13]. Unlike directed analysis, it avoids limitations imposed through existing theories, fostering a rich and context-specific understanding [14]. Using this method, the study systematically refined an initial pool of 271 papers to 41, identifying key risks and categories associated with integrating GenAI in CRM for SCPs.

2.2 *Stage two: risk evaluation*

A questionnaire was developed to measure risk significance using (1) the probability level (PL), which measured the likelihood of the risk arising based on factors such as expert availability (*ea*) and organisation's technological maturity (*otm*); (2) the impact level (IL) on project and organisation, project cost (*ipc*), schedule (*ips*), and organisational reputation (*ior*). A five-point Likert scale from very low to very high was used. 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.

2.3 *Stage three: risk quantification*

Fuzzy Set Theory (FST), introduced by Zadeh (1996), extends classical set theory by providing a framework for addressing uncertainty and imprecision in decision-making [15]. 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" [16]. This research utilised three fuzzy controllers to assess risk significance. The first controller evaluated the IL of each risk based on its components: *ipc*, *ips*, and *ior*. The second controller measured the PL using *ea* and *otm*. Finally, the third and main controller computed the overall risk significance which represented as fuzzy risk number (F-RN) through integrating the two primary assessment criteria (i.e., IL and PL). Additionally, in each controller, the risk assessment criteria and their respective components were transformed into fuzzy sets using predefined triangular membership functions as shown in Figure 2. The architecture of the proposed GenAI risk assessment model is structured around three essential processes: (1) the fuzzification process, where both input and output variables are represented using triangular membership functions. This choice is guided by the functions' simplicity, computational efficiency, and effectiveness in capturing subjective and imprecise expert knowledge, which has led to their widespread adoption in similar fuzzy modelling applications [17]; (2) the inference stage, where Mamdani Fuzzy Inference System is employed due to its intuitive reasoning capabilities, ability to handle linguistic variables, and strong prevalence in engineering and decision-making literature [18]; and (3) the defuzzification process, which is carried out using the centroid of area method, 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 [19].

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 illustrates an example of the output risk significance membership functions.

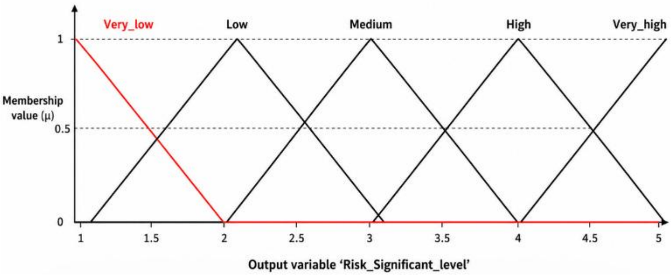

Figure 2. Membership functions for risk significance level

3 RESULTS AND DISCUSSION

3.1 Identified socio-technical risks

The SLR identified 12 key socio-technical risks associated with integrating GenAI into CRM. These risks are outlined in Table 1, along with their respective sources and definitions. They are driven by human capability, behaviour, and societal expectations, including trust, fairness, privacy, accountability, and regulation when using GenAI in CRM.

Table 1. Identified socio-technical risks

Risk	Definition	Sources
R01. Insufficient training	Users lack the skills to operate GenAI tools properly, which increases misuse, overreliance, and poor risk decisions.	[10], [11], [12], [13], [26]
R02. Absence of expertise	Lack of specialist AI/risk expertise reduces the quality of configuration, validation, and governance.	[15],[16], [18],[26], [29],[35]
R03. Misinterpretation of results	Users may treat GenAI outputs as facts, ignore uncertainty, or misunderstand recommendations.	[19], [20], [21],[27], [30],[34]
R04. Lack of awareness	Stakeholders may not understand GenAI limitations/risks, weakening critical judgement and controls.	[10], [11], [12], [6], [13],[1], [40]
R05. Cultural resistance	Resistance to change reduces adoption, consistency, and collaboration in risk processes.	[18],[22], [23],[24], [31],[36], [41]
R06. Lack of trust	Low trust in GenAI insights can lead to rejection, conflict, or practices outside governance.	[19],[20], [24], [25]
R07. Algorithm bias	Biased outputs can produce unfair prioritisation and harm legitimacy, equity, and stakeholder confidence.	[17],[19], [21],[35], [37]
R08. Absence of regulatory frameworks	Unclear/limited standards create uncertainty about acceptable use, auditability, and compliance.	[15],[16], [26],[32], [33]
R09. Confidentiality breach	Sensitive project/organisational information may be exposed, damaging relationships and trust.	[13],[28], [17],[35]
R10. Unclear responsibility and accountability	Ambiguity over who is accountable for GenAI-informed decisions weakens governance and liability management.	[22],[26], [13],[29], [30],[31], [37]
R11. Incompliance with data privacy policies	Use of GenAI may breach internal privacy rules and related obligations, creating legal/trust consequences.	[22],[27], [25],[29] [32]
R12. Data breach	Security incidents can expose sensitive/personal data and undermine public and stakeholder confidence.	[17],[23], [24],[32], [38],[39]

3.2 Architecture of the developed risk assessment model

The proposed risk assessment model was designed using three fuzzy controllers via MATLAB R2024b [42], with each controller dedicated to evaluating a specific risk dimension. Figure 3 illustrates the architecture of the proposed risk assessment model.

To this end, the mean values of *ipc*, *ips*, *ior*, *ae*, *otm*, and were used as crisp inputs, as presented in columns 2 to 6 of Table 2. 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 was computed, represented as F-RN, along with its ranking, as shown in columns 7 and 8 of Table 2

Table 2. Fuzzy analysis results

Risk ID	Probability level		Impact level			(FRN)	Overall rank
	ea	*otm*	*ipc*	*ips*	*ior*		
R01	3.59	3.34	3.54	3.55	3.47	3.61	1
R02	3.51	3.34	3.86	3.75	3.69	3.51	5
R03	3.49	3.31	3.81	3.77	3.79	3.49	6
R04	3.56	3.36	3.51	3.49	3.45	3.56	3
R05	3.23	3.22	3.04	3.12	3.23	3.23	11
R06	3.38	3.29	3.03	3.18	3.35	3.38	9
R07	3.29	3.14	3.30	3.24	3.32	3.29	10
R08	3.41	3.11	3.51	3.40	3.48	3.41	8
R09	3.45	3.45	3.40	3.44	3.92	3.45	7
R10	3.55	3.26	3.51	3.55	3.56	3.55	4
R11	3.45	3.36	3.36	3.38	3.59	3.45	7
R12	3.59	3.03	3.68	3.47	4.03	3.59	2

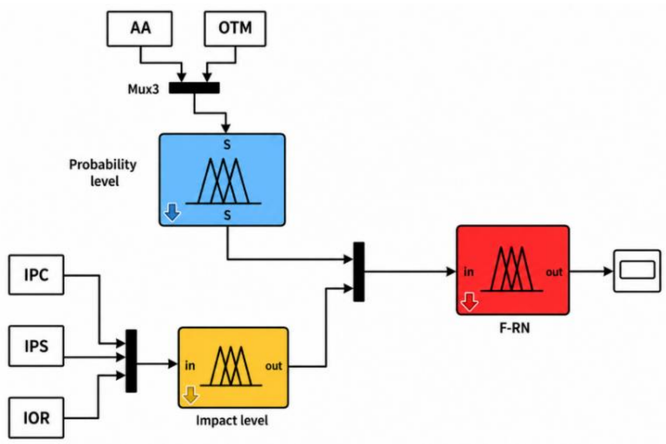

Figure 3. Proposed fuzzy based risk assessment model

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, Figure 4 represent the dependencies for each controller, where each surface plot includes two input variables and one output variable specifically, for impact, probability and overall significance level.

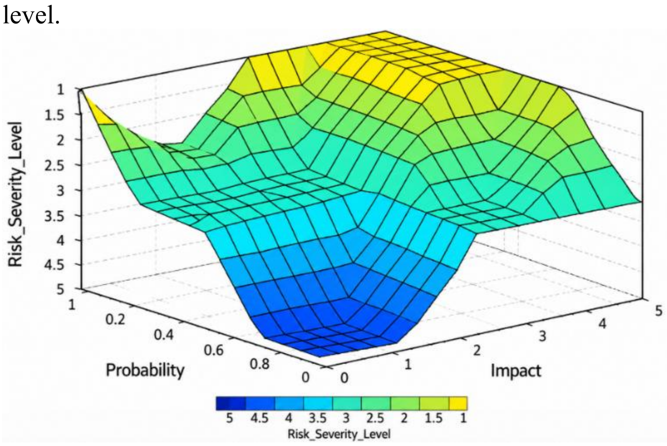

Figure 4. Surface plot of risk significance level

3.3 Risk prioritisation results

Socio-technical risks describe the vulnerabilities that emerge when GenAI is applied within CRM, and its outputs are shaped under human judgement, organisational routines, and governance conditions. This paper concentrates on one socio-technical category because the most important threats are produced through interaction effects rather than isolated technical faults. GenAI tools depend on users to frame queries, judge credibility, and translate outputs into risk responses, and they depend on organisational decisions about oversight, accountability, and data protection. For example, in sustainable construction projects this interaction is especially important because risk decisions influence safety performance, public confidence, contractual relationships, and long-term outcomes. Socio-technical risks therefore capture the practical reality that GenAI enabled risk management functions as a shared system where technology, people, and institutions jointly determine decision quality. The fuzzy analysis provides a clear prioritisation of these socio-technical risks and shows that the highest ranked threats cluster around workforce capability and information security exposure. The most critical risk is R01 insufficient training, ranked first with an F-RN value of 3.61, indicating that user readiness is the strongest driver of vulnerability. Training gaps increase the likelihood of weak prompting practices, poor verification, and inconsistent application of recommendations across teams, while also reducing the ability to recognise uncertainty and limitations in model outputs [2]. When GenAI supports risk identification, assessment, and response planning, training weaknesses can lead to systematic misapplication rather than isolated mistakes, which helps explain why R01 sits at the top of the ranking [4]. The second highest risk is R12 data breach, ranked second with an F-RN value of 3.59, highlighting that security compromise is a major socio-technical threat because GenAI use is tightly coupled with large volumes of sensitive project information [17]. CRM routinely handles commercially sensitive data, incident records, design and site information, and stakeholder communications. A breach can create immediate disruption and loss of confidentiality, alongside longer-term consequences such as reputational damage and reduced willingness to share information across partners. In multi-party delivery models, impacts can propagate across the supply chain and undermine collaboration, which is essential for effective risk management. The high rank of R12 indicates that socio-technical risk is strongly shaped by secure data handling across human and organisational boundaries, not only model behaviour.

Furthermore, R04 lack of awareness is ranked third with an F-RN value of 3.56, reinforcing the importance of human factors at a broader level than training alone. Lack of awareness includes limited understanding of what GenAI can and cannot do, weak recognition of when outputs require validation, and incomplete appreciation of privacy and ethical duties. A user may operate a tool yet still lack the awareness needed to interpret output safely and contextually, which can lead to overconfidence, inappropriate reliance, and reduced challenge during risk workshops and decision meetings. R10 unclear responsibility and accountability is ranked fourth with an F-RN value of 3.55, pointing to a governance weakness that becomes more acute when GenAI supports decisions with contractual, safety, or public value consequences. Construction projects already distribute responsibility across clients, designers, contractors, and specialist suppliers, and GenAI can blur boundaries further if accountability is not explicitly defined for tool selection, data preparation, output validation, and approval of final decisions. When responsibility is unclear, controls weaken because assumptions form that someone else is checking the system, and stakeholders may reject recommendations when the assurance chain is not transparent or owned. The next ranked risks deepen the capability and interpretation picture. R02 absence of expertise is ranked fifth with an F-RN value of 3.51, and R03 misinterpretation of results is ranked sixth with an F-RN value of 3.49, reflecting specialised weaknesses that sit alongside training and awareness. Absence of expertise signals limited specialist capacity to configure tools, define suitable use cases, establish validation routines, and set thresholds for reliance. Misinterpretation reflects the practical challenge that GenAI outputs can appear convincing while remaining incomplete, overly generic, or misaligned with project context, leading to incorrect prioritisation, ineffective mitigation, or a false sense of control when outputs are accepted as authoritative without cross checking against site conditions, contract requirements, and stakeholder constraints [2]. Two closely related risks share seventh place with the same F RN value of 3.45, namely R09 confidentiality breach and R11 noncompliance with organisational data privacy policies, showing that stakeholders view privacy discipline as a core condition for responsible adoption. These risks also connect strongly with R12, since breach events often follow earlier weaknesses in routine confidentiality practices and policy compliance. R08 absence of regulatory frameworks is ranked eighth with an F RN value of 3.41, highlighting uncertainty around standards, audit expectations, and defensible practice for AI supported risk management. The remaining risks relate to adoption stability and legitimacy, with R06 lack of trust ranked ninth at 3.38, R07 algorithm bias ranked tenth at 3.29, and R05 cultural resistance ranked eleventh at 3.23.

To this end, the fuzzy ranking indicates that socio-technical risk management should prioritise training and awareness, secure handling of project data, and clear accountability structures, supported with expertise development, privacy compliance, and trust building measures. The most severe socio-technical risks arise when human capability is insufficient and when governance and security controls do not adequately protect sensitive information or clarify responsibility for GenAI supported judgements, so strengthening these areas supports more reliable interpretation of outputs, higher quality risk responses, and greater stakeholder confidence in GenAI enabled CRM.

4 CONCLUSION

This study examined the socio-technical risks associated with integrating GenAI into CRM. Using a three-stage methodology involving a systematic literature review, expert survey, and fuzzy set theory-based assessment model, twelve key risks were identified, quantified, and ranked. The findings show that insufficient training is the most significant risk, followed by data breach, lack of awareness, and unclear responsibility and accountability. These results indicate that GenAI adoption in CRM is strongly influenced by workforce readiness, secure data governance, and clear decision accountability.

The study contributes to the CRM literature by providing a structured understanding of GenAI-related socio-technical risks and demonstrating how fuzzy set theory can support risk prioritisation under uncertainty. Practically, the findings suggest that construction organisations should prioritise targeted training, awareness programmes, data protection protocols, privacy compliance, and clearly defined accountability structures before deploying GenAI tools in risk management processes. Overall, responsible GenAI integration in CRM requires more than technical implementation. It requires coordinated attention to people, organisational governance, data security, and ethical decision-making. Future studies may extend this work by validating the proposed model in different countries, project types, and organisational settings, as well as by exploring mitigation strategies for the highest-ranked risks.

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