Generative AI in Construction Risk Management:
A Bibliometric Analysis of the Associated Benefits and Risks

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Abstract

Purpose: The construction industry is under increasing pressure to improve risk management due to the complexity and uncertainty inherent in its projects. Generative AI (GenAI) has emerged as a promising tool to address these challenges, however, there remains limited understanding of its benefits and risks in Construction Risk Management (CRM). This study conducts a bibliometric analysis of current research on GenAI in CRM, exploring publication trends, citations, keywords, intellectual linkages, key contributors, and methodologies.

Design/methodology/approach: A review of Scopus publications from 2014 to 2024 identifies key categories of GenAI’s benefits and risks for CRM. Using VOSViewer, visual maps illustrate research trends, collaboration networks, and citation patterns.

Findings: The findings reveal a notable increase in research interest in GenAI for CRM, with benefits classified into technical, operational, technological, and integration categories. Risks are grouped into nine areas, including social, security, data, and performance.

Research limitations/implications: Despite its comprehensive scope, this research focuses exclusively on peer-reviewed articles published between 2014 and 2024, potentially excluding relevant studies from outside this period or non-peer-reviewed sources. Additionally, the bibliometric analysis relied on a specific set of keywords, which may have excluded articles using alternative terminology for GenAI or categorized under related fields.

Practical implications: The categorisation of GenAI risks in CRM provides a foundation for critical risk management processes, such as risk analysis, evaluation, and response planning. Additionally, understanding the identified benefits, such as improved risk prediction, alongside associated risks, such as ethical and data security issues, enables practitioners to balance innovation with caution, ensuring effective and responsible adoption of GenAI technologies.

Originality/value: This research offers a novel bibliometric analysis of the benefits and risks of GenAI in CRM, providing a comprehensive understanding of the field's evolution and global research landscape. Through the categorisation of the benefits and risks of GenAI in CRM, the study lays the groundwork for developing comprehensive risk management models. Additionally, it identifies key methodologies and research trends, enabling academics and practitioners to refine approaches and bridge research gaps. This work not only enhances theoretical insights but also provides actionable strategies for integrating GenAI into CRM practices effectively and responsibly.

Keywords: Generative AI, Benefits and Risks, Risk Management, Construction Management, Construction Industry

1. Introduction

The construction industry is increasingly recognising the need for advanced risk management due to the inherent complexities and dynamic nature of its projects (Al-Mhdawi et al., 2022; Chenya et al., 2022). Traditional AI-based risk management strategies predominantly employ complex mathematical models that mandate advanced statistical coding skills (Addo et al., 2020). While such models exhibit significant computational prowess, they inadvertently imbue the risk management process with additional complexities (Al-Mhdawi et al., 2023). Consequently, project managers often resort to subjective judgments when confronted with pivotal risk-related decisions. This reliance on intuition over structured analysis engenders a latent ambiguity, amplifying the uncertainty and potential biases within decision-making frameworks. Extant research underscores this phenomenon (e.g., Cox, 2008; Ball and Watt, 2013; Thomas et al., 2014; Al-Mhdawi et al., 2024), illustrating how a subjective approach may adversely impact both the efficacy and precision of risk management modalities.

In contrast, Generative Artificial Intelligence (GenAI) constitutes a tentative alternative, employing advanced algorithms and machine learning modalities to dynamically analyse vast amounts of data in real-time (Dacre & Kockum, 2022; Mandapuram et al., 2018). Such capabilities afford GenAI the potential to deliver predictive insights and adaptive risk management strategies, which are indispensable for addressing multilayered risks including cost overruns, delays, safety hazards, and resource allocation challenges (Mohammed and Skibniewski, 2023). Unlike conventional AI, GenAI operates through a continuously evolving model, enabling enhanced predictive accuracy and decision-making capabilities over time (Dacre & Kockum, 2022; Yan et al., 2024). Thus, the integration of GenAI into Construction Risk Management (CRM) emerges as critically significant for supporting the resilience and operational efficiency of construction project management (Ghimire et al., 2023; Manh et al., 2024). Moreover, GenAI offers a compelling approach to the inherent limitations in traditional risk management approaches (Zhao, 2024). It leverages cutting-edge algorithms and machine learning techniques to analyse extensive datasets dynamically (Vijayalakshmi and Thiyagarajan, 2023; Himeur et al., 2023). GenAI excels in devising adaptive risk strategies crucial for managing complex issues, including cost overruns, project delays, and quality deficiencies (Regona et al., 2022). Unlike the relatively static models of conventional AI, GenAI's continuous learning mechanism enhances both predictive accuracy and strategic efficacy with each iteration, underscoring its transformative impact on CRM. As such, the integration of GenAI into CRM transcends mere operational benefit, representing a pivotal shift toward greater resilience and operational efficiency within construction project management (Mohammed and Skibniewski, 2023).

Despite the perceived benefits of GenAI for managing risks in construction projects, several substantial risks related to data security, privacy, governance, skills gap, and regulatory compliance need careful consideration (Osmeni and Ali, 2023; Schneider et al., 2024; Gupta et al., 2023). The integration of GenAI into construction relies heavily on vast quantities of sensitive data, ranging from architectural plans to financial records. This data dependency raises significant concerns about data security (Parveen, 2018), as unauthorised access or breaches could lead to severe financial and reputational damage. Additionally, maintaining privacy becomes challenging as the data often contains confidential information about clients and stakeholders. Data governance also becomes a critical issue, requiring clear policies on data usage, storage, and disposal to ensure integrity and compliance with legal standards (Adekunle et al., 2022). Furthermore, the rapidly evolving nature of GenAI in industries like construction often outpaces existing regulatory frameworks, highlighting Industry 5.0 concept's emphasis on developing resilient and human-centric systems to navigate such technological advancements effectively (Dacre et al., 2024). Companies must navigate a labyrinth of laws that may not fully address the nuances of AI, leading to potential legal risks (Atkinson and Morrison 2024). Firms must establish rigorous compliance programs and continuously monitor regulatory developments to ensure their use of GenAI aligns with current laws and ethical standards (Pillai and Matus 2020). Thus, while GenAI offers transformative potential in risk management for construction projects, it also demands a heightened focus on these critical areas to safeguard its benefits effectively.

Substantial efforts have been invested in developing and testing GenAI models across various engineering disciplines, however a significant lack of consensus remains regarding the specific benefits and, more critically, the risks associated with deploying GenAI technologies in CRM. This uncertainty is further compounded by the diverse nature of the construction industry (Aladag, 2023), which encompasses a broad range of project types, from residential buildings to large-scale infrastructure projects. Each type presents unique challenges and specific requirements for the effective implementation of technology (Anysz et al., 2021; Parveen, 2018). CRM involves a complex network of stakeholders—including project managers, consultants, contractors, and safety officers—whose diverse expectations and experiences concerning GenAI's role in risk management highlight the broader institutional challenges that arise when traditional governance structures clash with the demands of implementing innovative methodologies, resulting in significant obstacles to effective integration (Baxter et al., 2023). These varied perspectives can lead to conflicting priorities and contribute to ambiguity regarding the perceived benefits and potential risks associated with GenAI adoption in CRM (Chenya et al., 2022). Additionally, the regulatory landscape varies significantly across regions, further influencing the feasibility, scope, and implementation of GenAI applications within construction risk management (Taiwo et al., 2024). Given this highly volatile and dynamic environment, the construction industry is well-suited for examining both the potential advantages and emerging risks of GenAI within CRM. The evolving nature of project management practices, including Agile Project Management, highlights the need for adaptive approaches to meet these challenges effectively (Dong et al., 2024). Effective CRM is increasingly essential for achieving project success, enhancing operational efficiency, optimising costs, and safeguarding worker safety, highlighting the importance of adopting broader models of project success (Dacre, Eggleton, Cantone, et al., 2021; Dacre, Eggleton, Gkogkidis, et al., 2021; Eggleton et al., 2021, 2023). Moreover, as research on GenAI applications in construction continues to gain interest, there remains a lack of studies that systematically examine both the benefits and risks of GenAI in CRM. Previous research has primarily focused on isolated aspects of AI applications, such as predictive analytics, automation, or safety enhancements (Jallow et al., 2023; Regona et al., 2022). However, these studies fail to provide a comprehensive and quantitative overview of GenAI's dual impact its opportunities and emerging risks within the dynamic construction industry context. By conducting a bibliometric analysis, this study addresses these gaps by systematically mapping research trends, identifying thematic areas, and offering insights into global contributions. Such an analysis provides a foundation for future research directions and ensures a balanced understanding of GenAI's role in CRM. Recognising GenAI’s dual impact, such as its capacity to enhance construction risk management (Jallow et al., 2023) alongside the introduction of new technology-related risks (Chenya et al., 2022), points to the impetus for a comprehensive bibliometric analysis. This would deliver a deep quantitative overview of current research trends, identify key thematic areas, evaluate the influence of foundational works, and assess the geographic and institutional spread of research contributions within this rapidly evolving field of research and practice.

Bibliometric analysis is a quantitative method widely employed in academia to systematically examine scientific literature. This technique enables the thorough evaluation of extensive academic outputs, analysing publication history, characteristics, and the developmental trajectory of research within a particular field through quantitative metrics (Akinlolu et al., 2022; Guray and Kismet, 2023). It assesses the performance and trends in scholarly contributions from individuals, journals and institutions, revealing collaboration patterns that underscore the matrix within the academic community (Waltman, 2016). This type of analysis identifies key influencers, pivotal studies, and primary publication venues, highlighting the central figures and institutions driving a field (Liang and Shi, 2022). Furthermore, bibliometric analysis explores the breadth of research themes and encourages interdisciplinary insights by assessing contributions across various journals and subject areas (Lu and Zhang, 2022; Aliu and Aigbavboa, 2023). It also identifies emerging developments and shifts in focus within a discipline, often uncovering new research directions and topical trends (Aria and Cuccurullo, 2017; Cobo et al., 2011). Moreover, bibliometric analysis identifies research gaps, highlighting areas that lack sufficient study or geographic representation, thereby informing future research directions (Passas, 2024). This analysis is crucial for decision-making in academia and research governance, including the assessment of journal and institutional performance. Additionally, it serves as a valuable tool for policymakers and funding agencies, aiding in the strategic distribution of research grants and resources based on empirical data (Lunny, 2022).

To this end, this research seeks to answer the following research questions:

RQ1: What are the key publication trends and intellectual connections in GenAI research for CRM between 2014 and 2024?

RQ2: What are the prevalent themes and methodologies in identifying the benefits and risks of GenAI in CRM?

RQ3: What are the primary categories of benefits and risks of GenAI in CRM based on current research?

This bibliometric research offers an in-depth analysis of the development and current state of studies on the benefits and risks of GenAI in CRM. It identifies key publications, authors, institutions, and methodologies while highlighting research gaps and potential areas for future collaboration. The study emphasises the practical value of understanding GenAI's benefits and risks for stakeholders, aiding decision-making in integrating these technologies.

The paper is structured as follows: Section 2 introduces the research methodology adopted for data collection, analysis, and processing. Section 3 presents the results of the analysis and discusses the key findings. Finally, Section 4 provides the conclusions of the research.

2. Research Methodology

In this research, the authors adopted a three-step method for literature collection and analysis, as illustrated in Figure 1. This method builds on the approaches outlined by Hong et al. (2012), Osei-Kyei and Chan (2015), Siraj and Fayek (2013), and Al-Mhdawi (2024). This method was used to conduct a bibliometric analysis and identify key benefit and risk categories of GenAI in CRM. The three steps include: (1) search and identification of academic journals, (2) keyword identification and article selection, and (3) content analysis. Detailed descriptions of each step are provided in the following subsections.

Step one: Search engines and identification of academic journals

Multiple databases were employed to identify relevant journal articles, including ASCE Library, Emerald Insight, Google Scholar, IEEE Xplore, ScienceDirect, Scopus, Springer, Taylor & Francis, and Web of Science. These databases were chosen due to their comprehensive coverage of relevant research disciplines and their established use in comparable literature-based studies within construction management research. The selection of target journals for this study was based on the following criteria: (1) the journals 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, recognised for their significant influence in shaping construction management research. An exception was made for a paper from the European Safety and Reliability Conference due to its strong relevance and close connection to the subject of this study.

Step two: Keywords identification and articles selection

In this stage, a comprehensive search was conducted using the title/abstract/keyword (T/A/K) fields in the Scopus search engine. The search strategy used Boolean operators (e.g., AND, OR) to refine and broaden the keyword set. The keyword search included terms such as 'GenAI risks OR Generative Artificial Intelligence challenges,' 'GenAI benefits AND CRM,' and 'machine learning OR AI-generated models.' Variations such as 'Generative Artificial Intelligence,' 'transformative AI,' and 'AI models for risk management' were also incorporated to capture diverse terminologies. Similarly, for CRM, terms such as 'Construction Risk Management,' 'project risk control,' and 'construction risk strategies' were included to ensure comprehensive coverage of relevant literature. Papers containing these terms in the title, abstract, or keywords were deemed suitable for further analysis. An additional search was conducted using identical keywords across various databases, including the ASCE Library, Emerald Insight, Google Scholar, IEEE Xplore, ScienceDirect, Springer, Taylor & Francis, and Web of Science, aiming to identify articles discussing the benefits and risks associated with implementing GenAI in CRM. These databases were chosen because they are well-regarded for their comprehensive coverage of AI technologies and their applications in risk management and construction, ensuring a diverse and credible selection of relevant literature. Furthermore, articles addressing the development and training of GenAI models to enhance and refine AI capabilities for improving CRM processes, or related management procedures indirectly impacting risk management in construction projects, were also considered.

Step three: Content analysis

According to Hsieh and Barman et al. (2021), content analysis can be approached in three distinct ways: conventional, directed, and summative. This study employed a conventional content analysis method, which adopts an open-ended approach to data, allowing categories to naturally emerge without preconceived frameworks (Blomkvist, 2015). This approach is applicable to both qualitative and quantitative analysis, with newer variations such as reception-based and interpretive content analysis (Ahuvia, 2001). Conventional content analysis was chosen for this study because it allows for an open-ended, data-driven approach, which is ideal for exploring the relatively new topic of integrating GenAI into CRM. Unlike directed analysis, which relies on existing frameworks, conventional content analysis facilitates the identification of detailed themes directly from the data, ensuring that the categories of benefits and risks emerge naturally (Kibiswa, 2019). This method's flexibility enables a deep, context-rich understanding, which is particularly valuable for evaluating the relevance of articles and capturing insights beyond preconceived notions (Hsieh and Shannon, 2005; Krippendorff, 2018). For an emerging field like GenAI in CRM, this approach supports a comprehensive exploration without imposing limitations from established theories. To this end, the authors conducted conventional content analysis to (1) identify key categories of benefits and risks associated with integrating GenAI into CRM, and (2) evaluate the articles' relevance for further analysis.

3. Results and Discussion

3.1 Annual publication analysis

In this step, an annual publication analysis was conducted to evaluate the number of articles published each year, focusing on the activity surrounding a specific topic over a defined timeframe. This analysis provides insights into the evolution, knowledge accumulation, and maturity of the topic (Patnaik and Suar, 2019). The authors applied specific inclusion criteria, as outlined in the research methodology, to identify suitable journals. Subsequently, in step two, keywords, title, and article selection criteria were used to locate 473 papers related to GenAI in CRM published between 2014 and 2024. The initial screening of papers involved reviewing their titles and abstracts to determine relevance. Exclusion criteria were applied to remove articles unrelated to GenAI in CRM, such as studies focusing solely on traditional AI applications or unrelated risk management fields. Duplicate articles identified across databases were systematically excluded. To ensure data quality, an iterative review process was employed, involving multiple rounds of evaluation and discussion among the authors to resolve any doubts. Articles that did not meet the inclusion criteria or were redundant were excluded at each stage. This approach helped to ensure consistency and minimise bias in selecting the most pertinent studies. Ultimately, only 55 papers specifically addressing the benefits and risks of GenAI in CRM were identified. The 55 selected articles, as shown in Table 1, reveal that 23.64% of the research on the benefits and risks of GenAI in CRM was conducted between 2014 and 2019, while 76.36% was published between 2020 and 2024. This shift highlights a growing trend in studying the opportunities and impacts of implementing GenAI in CRM, as well as the challenges associated with integrating GenAI into CRM. Additionally, Figure 2 illustrates the publication frequency over the period from 2014 to 2024, with each data point representing the number of publications per year. The figure illustrates a steady increase in publications, ending in almost exponential growth starting in 2023. This trend reflects the growing recognition of GenAI's transformative potential in CRM, likely driven by advancements in AI technologies and increased digitalisation in the construction industry. The surge in 2023 may also be attributed to global initiatives promoting AI adoption in construction and an uptick in funding for AI-driven research. These trends suggest that CRM is becoming a focal point for leveraging AI, particularly as industries seek innovative solutions to address complexity and uncertainty.

Table 1. Number of articles in year range

Year	Used articles	Number of articles
2014 - 2019	Costantino (2015), Whyte et al. (2016), Kulkarni et al. (2017), Wu et al. (2017), Zou et al. (2017), Louis, and Dunston (2018), Poh et al. (2018), Farooq et al. (2018), Guo et al. (2018), Hung (2018), Parveen (2018), Lachhab (2018), Hu and Castro (2019)	13
2020 - 2024	Boughaba, and Bouabaz (2020), Eber (2020), Lee and Shin (2020), Yaseen et al. (2020), Pillai and Matus (2020), Anysz et al. (2021), Abioye et al. (2021), Pan and Zhang (2021), Afzal et al. (2021), Davahli et al. (2021), An et al. (2021), Prebanic and Vukomanovic (2021), Choi, et al. (2021), Tang and Golparvar, (2021), Adekunle et al. (2022), Regona et al. (2022), McMillan and Varga (2022), Chenya et al. (2022), Erfani and Cui (2022), Lin et al. (2022), Yigitcanlar et al. (2022), Holzmann and Lechiara (2022), Wijayasekera et al. (2022), Al-Mhdawi et al. (2023), Aladag (2023), Jallow et al. (2023), Fridgeirsson et al. (2023), Hashfi and Raharjo (2023), Waqar et al. (2023), Barcaui and Monat (2023), Pham and Han (2023), Giraud et al. (2023), Lee et al. (2023), Zhou et al. (2023), Gupta et al. (2023), Chou et al. (2024), Nabawy and Gouda (2024), Liang et al. (2024), Jang and Lee (2024), Zhao (2024), Muller et al. (2024), Nyqvist et al. (2024)	42

3.2 Most frequently cited journals and papers

The significance of frequently cited journals and papers lies in their ability to reflect key research trends, priorities, and impacts within a field. Citation analysis offers valuable insights into the most influential authors, articles, and journals, which in turn shape academic reputations and guide future research directions (Wong et al., 2013). However, it is important to note that citation-based metrics may be influenced by factors unrelated to research quality. For instance, open-access journals tend to have higher citation counts due to their wider accessibility, which may skew comparisons with subscription-based journals. To identify the most frequently cited journals in the selected papers that examine the risks and benefits of GenAI in CRM, we used three key indicators: Total Papers (TP), Total Citations (TC), and Total Citations per Paper (TCP). The primary measure for determining journal popularity was TP, while TC was used to rank journals in cases where the TP count was the same.

The analysis covered 55 articles published in 27 different journals, along with one conference paper, as outlined in the research methodology. The results show that "Automation in Construction" had the highest number of published papers, contributing 9 articles (16.36% of total publications), with a total citation count of 1,194, averaging 132.67 citations per paper.

Additionally, the "*Sustainability*", "*Journal of Computing in Civil Engineering*" and "*Engineering Applications of Artificial Intelligence*" each published 4 papers (7.27%). Among these, the "*Sustainability*" had the highest total citation count at 390. Table 2 provides a detailed breakdown of the most frequently cited journals. Furthermore, Figure 3 illustrates the contributions of various journals to the selected research, focusing on publication trends from 2014 to 2024. The figure highlights that most journals increasingly contributed to research on the benefits and risks of implementing GenAI in CRM, especially between 2020 and 2024.

Table 2. Most contributing journals

R	Journal	TP	TC	TCP
1	Automation in Construction (AC)	9	1194	132.67
2	Sustainability	4	390	97.5
3	Journal of Computing in Civil Engineering (JCCE)	4	111	27.75
4	Engineering Applications of Artificial Intelligence (EAAI)	4	64	16
5	International Journal of Project Management (IJPM)	3	657	219
6	International Journal of Construction Management (IJCM)	3	37	12.33
7	Journal of Open Innovation (JOI)	2	212	106
8	IEEE Access (IEEEA)	2	160	80
9	Symmetry	2	43	21.5
10	Project Management Journal (PMJ)	2	19	9.5
11	Applied Sciences (AS)	2	19	9.5
12	Frontiers in Built Environment (FBE)	2	5	2.5
13	Journal of Building Engineering (JBE)	1	382	382
14	Business Horizons (BH)	1	330	330
15	International Journal of Managing Projects in Business (IJMPB)	1	102	102
16	Journal of Soft Computing in Civil Engineering (JSCCE)	1	82	82
17	International Journal of Civil Engineering and Technology (IJCET)	1	38	38
18	Organization, Technology & Management in Construction (OTMC)	1	31	31
19	Science and Public Policy (SPP)	1	25	25
20	Journal of Civil Engineering and Management (JCEM)	1	22	22
21	Journal of Science and Technology in Civil Engineering (JSTCE)	1	12	12
22	The 33rd European Safety and Reliability Conference (ESRC)	1	10	10
23	European Journal of Business and Management Research (EJBMR)	1	8	8
24	International Journal of Advanced Computer Science and Applications (IJACSA)	1	5	5
25	Project Leadership and Society	1	5	5
26	Engineering Management journal (EMJ)	1	4	4
27	Advances in Computational Design (ACD)	1	4	4
28	Engineering, Construction and Architectural Management (ECAM)	1	0	0

R=Rank; TP =Total papers; TC = Total citations; TCP= Total citations per paper

To identify the most highly cited articles, we calculated the Normalised Number of Citations (NNC) by dividing the total number of citations each paper received by the number of years since its publication (Al-Mhdawi et al., 2024). This normalisation analysis ensures a fair comparison of citation impact across papers published at different times, as it prevents older articles, which have had more time to accumulate citations, from having an undue advantage over newer ones (Al-Mhdawi et al., 2024). The NNC analysis revealed that Pan and Zhang (2021) had the highest impact, with an NNC of 154.3, followed by Abioye et al. (2021) with an NNC of 82.7, and Gupta et al. (2023) with an NNC of 61. Table 3 lists the ten most frequently cited articles, ranked by their citation frequency.

Table 3. Most frequently cited papers

Author/year	Paper title	TC	NNC	R
Pan and Zhang (2021)	Roles of artificial intelligence in construction engineering and management: A critical review and future trends	463	154.3	1
Abioye et al. (2021)	Artificial intelligence in the construction industry: A review of present status, opportunities, and future challenges	248	82.7	2
Lee and Shin (2020)	Machine learning for enterprises: Applications, algorithm selection, and challenges.	181	45.3	5
Costantino et al. (2015)	Project selection in project portfolio management: An artificial neural network model based on critical success factors	150	16.7	9
Whyte et al. (2016)	Managing change in the delivery of complex projects: Configuration management, asset information and 'big data	138	17.3	7
Poh et al. (2018)	Safety leading indicators for construction sites: A machine learning approach.	182	30.3	6
Regona et al. (2022)	Opportunities and adoption challenges of AI in the construction industry: A PRISMA review	148	74	4
Zou et al. (2017)	Retrieving similar cases for construction project risk management using Natural Language Processing techniques	117	16.7	10
Gupta et al. (2023)	From ChatGPT to threat-GPT: Impact of generative ai in cybersecurity and privacy	61	61	3
Afzal et al. (2021)	A review of artificial intelligence-based risk assessment methods for capturing complexity-risk interdependencies: Cost overrun in construction projects.	58	19.3	8

Abbreviations: TC = Total citations; NNC= Normalised Number of Citations; R=Rank

3.3 Most common keyword occurrences

Identifying frequent keywords in article titles and abstracts is a valuable method for analysing research trends and topics in scientific literature. Bibliometric keyword analysis can reveal popular research areas and detect changes over time (Pesta et al., 2018). Additionally, keyword frequency analysis can be used to generate keyword clouds, visually representing the prominence of specific topics (Maki & Webster, 2018). For this reason, statistical metrics can be employed to identify important keywords by comparing their prevalence in a subset of documents against a broader background set (Dasigi et al., 2018).

In this research, the analysis of the most common keyword occurrences was conducted using two metrics: keyword occurrences (Oc) and keyword co-occurrences (Co) (Heersmink et al., 2011). Keyword occurrences are derived from terms provided by the authors and are extracted from the title, abstract, and citation contexts of the selected articles. A limitation of only considering keywords that appeared at least three times was applied. Keywords are considered co-occurring when two or more keywords appear together within the title, abstract, or citation context of the papers. The primary metric for assessing keyword frequency is the Oc measure. However, in cases where there is a tie in Oc, the ranking is determined by the Co measure.

As shown in Table 4, "artificial intelligence" is the most frequently occurring keyword, with 19 occurrences and 69 co-occurrences, indicating its central role in the research. "Project management" follows with 16 occurrences and 68 co-occurrences, highlighting its significant relevance. The "construction industry" ranks third, with 13 occurrences and 52 co-occurrences, demonstrating its substantial presence in the research field. This analysis suggests that these three keywords are pivotal in the discourse surrounding GenAI in CRM, reflecting their prominence and interconnectedness in the literature.

Table 4. Most common author keyword occurrences

R	Keyword	Oc	Co
1	Artificial Intelligence	19	69
2	Project Management	16	68
3	Construction Industry	13	52
4	Risk Management	13	67
5	Risk Assessment	11	58
6	Machine Learning	8	41
7	Decision Making	7	26
8	Artificial Intelligence (AI)	7	19
9	Natural Language Processing Systems	6	35
10	Risks Management	5	39
11	Learning Systems	5	38
12	Construction Projects	5	31
12	Deep Learning	5	31
13	Natural Language Processing	5	26
14	Data Mining	4	25
15	Semantics	4	24
16	Learning Algorithms	4	23
17	Accident Prevention	4	22
18	Decision Trees	4	17

19	Fuzzy Logic	4	9
20	Construction	4	6
21	Risk Analysis	3	21
22	Robotics	3	13
23	Industry 4.0	3	12
24	Neural Networks	3	11
24	Architectural Design	3	11
25	Construction Management	3	10
26	Automation	3	9
26	Big Data	3	9
26	Human Resource Management	3	9
27	Artificial Neural Network	3	8
28	Artificial Neural Networks	3	5

Abbreviations: Oc = Keywords occurrence; Co = keywords Co-occurrence; R=Rank

Merging synonymous terms such as 'artificial intelligence' and 'AI' or 'neural networks' and 'artificial neural networks,' would improve the clarity and cohesion of the keyword analysis significantly by creating interconnected clusters. These clusters reveal thematic focus areas such as AI-driven decision-making, risk prediction, and integration into CRM processes. This refined analysis not only enhances clarity but also highlights the interconnectedness of technical and managerial themes, suggesting opportunities for interdisciplinary research. In order to gain deeper insights, we employed VOSviewer software, which is widely regarded for its effectiveness in visualising complex bibliometric networks and relationships between keywords (Figure 4). VOSviewer was particularly suitable due to its capability to generate clear visual representations that reveal patterns and clusters within the data. In this visualisation, 'nodes' represent the frequency of keyword occurrences, with larger nodes indicating higher occurrence frequencies. 'Links' between nodes illustrate the relationships between keywords, with thicker lines signifying more frequent co-occurrences. Furthermore, shorter lines indicate stronger relatedness and closer proximity between keywords. Different colours are used to distinguish groups of co-occurring keywords, highlighting distinct clusters within the data, thus enhancing our understanding of the connections and emerging themes within the research field.

3.4 Bibliographic coupling of analysed journals

Bibliographic coupling, a method for measuring the similarity between documents based on shared references, has been extensively applied in various fields (Mubeen, 1995). It is particularly valuable as it identifies "centerness" in knowledge networks and facilitates the coalescence of information, complementing co-authorship networks (Youtie et al., 2013). Moreover, bibliographic coupling captures unique insights that co-authorship analysis may not, suggesting its value when used alongside other methods (Kleminski et al., 2020).

In this study, bibliographic coupling was employed to map the relationships between journals that published articles on the benefits and risks of GenAI. Figure 5 visualises this coupling, with each node representing a journal and different colours indicating clusters of closely related journals based on shared citations. These clusters highlight thematic groupings in GenAI risks and benefits in CRM research, reflecting distinct trends such as technical applications and socio-ethical aspects. For instance, the prominent cluster includes Automation in Construction, Journal of Computing in Civil Engineering, and IEEE Access, which share the focus on GenAI risks in construction management and practical training models to enhance its performance in CRM. Additionally, the strong citation relationships within this cluster suggest the formation of specialised communities dedicated to specific themes.

3.5 Most Contributing Authors

Analysing the most influential authors in scientific research is essential for understanding collaboration patterns, research leadership, and individual contributions within a specific domain. This analysis provides insights into how knowledge production is distributed and reveals the influence that certain individuals or groups have over the field. Additionally, it helps to map the intellectual structure of the research area, identifying key focal points of inquiry and demonstrating how influential figures are shaping the direction of research.

Table 5 presents the top ten researchers contributing to the field of GenAI in CRM. To determine the most influential authors, TP is used as the primary measure of research productivity. When authors have the same number of publications, TC is used to rank them, indicating the impact of their work. The analysis reveals that Regona M., Li R.Y.M., Xia B., and Yigitcanlar T. have consistently contributed to the field, with significant outputs and citation impacts over recent years, marking them as consistent leaders. Temporal patterns indicate a steady presence of these authors since 2020, reflecting their foundational roles in advancing the domain. Conversely, emerging contributors, such as Pan Y. and Zhang L., gained prominence in 2023 with high-impact publications addressing transformative applications of GenAI in CRM. This suggests a growing diversification of thought leaders, driven by an influx of researchers responding to the surge in interest and funding for AI technologies. Tang S., from Xiamen University in China, also has a TP of 2 but a much lower TC of 26, indicating that while their productivity matches the others, their work has received fewer citations.

Table 5. Most contributing authors

R	Author	Recent Affiliation	Country	TP	TC
1	Regona m.	Queensland University of Technology	Australia	2	148
1	Li r.y.m.	Hong Kong Shue yan university	Hong Kong	2	148
1	Xia b.	Queensland University of Technology	Australia	2	148
1	Yigitcanlar t.	Queensland University of Technology	Australia	2	148
2	Tang s.	Xiamen University	China	2	26
3	Zhao x.	Central Queensland University	Australia	2	12
4	Rahimian f.	Teesside University	United Kingdom	2	4
5	Pan Y.	Shanghai Jiao Tong University	China	1	463
5	Zhang I.	Huazhong University of Science and Technology	China	1	463
6	Abioye S.	University of the West of England	United Kingdom	1	284

Abbreviations: R=Rank; TP =Total papers; TC = Total citations

Figure 6 illustrates a VOSviewer density visualisation of leading authors, representing the density of contributions through varying colour intensities. Brighter areas on the map indicate a higher concentration of contributors (co-authors). The visualisation uses a colour gradient ranging from light green (indicating lower density) to yellow (indicating higher density) to convey the intensity of research contributions. This visualisation effectively highlights where research activity is most concentrated, clearly indicating the distribution and prominence of key researchers within the area of study.

3.6 Most Contributing Institutions

The contribution of each institution or organisation is determined based on the affiliation of the authors. For instance, if a paper is authored by three researchers, with two affiliated with University X and one affiliated with University Y, it will be counted as one contribution for University X and one contribution for University Y. Table 6 presents the institutions contributing in the periods between 2014–2019 and 2020–2024, while Table 7 shows the top 10 organisations that contributed to research on GenAI in CRM, presenting the TP per institution, TC, and the Quacquarelli Symonds (QS) university rankings, which highlight academic performance based on research output, impact, and global standing.

Queensland University of Technology (Australia) and Hong Kong Shue Yan University (Hong Kong) are high-output institutions with multiple papers and significant citation counts, reflecting their strong research focus on GenAI in CRM. In contrast, institutions like Nanyang Technological University (Singapore) and the University of the West of England (UK), despite producing fewer papers, have achieved exceptional citation impact with singular, highly influential publications. This highlights a balance between research productivity and impact, where institutions with lower output can rival or exceed the influence of high-output counterparts by focusing on groundbreaking studies. Texas A&M University (United States), despite also having two papers, has a lower citation count of 17 and a QS ranking of 351–400, suggesting less impactful research or newer publications. Nanyang Technological University (Singapore) stands out with just one paper but an impressive 472 citations, coupled with a high QS ranking of 15, indicating exceptional research quality and global reputation. The University of the West of England (United Kingdom), with one paper and 262 citations, also demonstrates strong research impact, although its QS ranking is much lower at 741–750, reflecting a disparity between research influence and global visibility.

Table 6. Academic institutions with the highest contributions to GenAI in CRM research

2014-2019					2020-2024				
R	**University**	**Country**	**TP**	**TC**	**R**	**University**	**Country**	**TP**	**TC**
1	National University	Singapore	1	185	1	Queensland University of Technology	Australia	2	153
2	University of Rome	Italy	1	153	2	Hong Kong Shue Yan University	Hong Kong	2	111
3	University of Reading	UK	1	139	3	Texas A&M University	USA	2	17
4	University of Liverpool	UK	1	117	4	Nanyang technological University	Singapore	1	472
5	Oregon State University	USA	1	81	5	University of the west of the England	UK	1	262
5	Purdue University	USA	1	81	5	Brunel university	UK	1	262
6	Indian Institute of Technology	India	1	48	5	Obafemi Awolowo University	Nigeria	1	262
7	National University of Sciences & Technology	Pakistan	1	46	6	Hank Yong national University	south Korea	1	183
8	Huazhong University	China	1	19	6	Western Illinois University	USA	1	183
8	China university of geosciences	China	1	19	7	University of Diyala	Iraq	1	85
9	University of Nebraska	USA	1	16	7	Lulea University of Technology	Sweden	1	85
9	Stockholm University	Sweden	1	16	7	Duy Tan University	Viet Nam	1	85
10	Prince Sultan University	KSA	1	15	7	Ton Duc Thang University	Viet Nam	1	85
-	-	-	-	-	8	Tennessee Tech University	USA	1	70
-	-	-	-	-	9	University of Electronic Science & Technology	China	1	58
-	-	-	-	-	9	University of Engineering & Technology	Pakistan	1	58
-	-		-	-	10	UCL	UK	1	29
-	-	-	-	-	11	Pohang University	south Korea	1	27
-	-	-	-	-	12	University of Illinois	USA	1	23

Abbreviations: R=Rank; TP =Total papers; TC = Total citations

Table 7. Top 10 academic institutions publishing on GenAI in CRM

R	Organisation	Country	TP	TC	QS
1	Queensland University of Technology	Australia	2	153	213
2	Hong Kong Shue Yan University	Hong Kong	2	111	154
3	Texas A&M University	United States	2	17	351-400
4	Nanyang Technological University	Singapore	1	472	15
5	University of the West of England	United Kingdom	1	262	741-750
5	Brunel University	United Kingdom	1	262	342
5	Obafemi Awolowo University	Nigeria	1	262	1668
6	National University of Singapore	Singapore	1	185	8
7	Hank Yong National University	South Korea	1	183	651-660
7	Western Illinois University	United States	1	183	201-250
8	University of Rome	Italy	1	153	132
9	University of Reading	United Kingdom	1	138	172
10	University of Liverpool	United Kingdom	1	117	165

Abbreviations: R=Rank; TP =Total papers; TC = Total citations; QS= Quacquarelli Symonds

3.7 Most Contributing Countries

The TP metric represents the number of articles published in a research field by a specific country. When an article involves multiple countries, it is attributed to all contributing countries rather than being assigned to a single one. Table 8 shows the contributions of various countries, including the total number of published papers and citations during the periods from 2014 to 2019 and from 2020 to 2024. The table demonstrates a significant increase in the number of published papers in the period from 2020 to 2024.

Table 8. Most contributing countries

Rank	Country	2014-2019		2020-2024		Total	
		TP	TC	TP	TC	TP	TC
1	United States	3	150	6	306	9	456
2	United Kingdom	2	256	5	308	7	564
3	China	2	35	4	84	6	119
4	South Korea	-	-	5	222	5	222
5	Australia	-	-	4	165	4	165
6	Hong Kong	-	-	3	167	3	167
7	Pakistan	1	46	2	61	3	107
8	Sweden	1	16	2	88	3	104
9	France	2	24	1	10	3	34
10	Taiwan	-	-	3	17	3	17
11	Singapore	1	185	1	472	2	657
12	Nigeria	-	-	2	267	2	267
13	Italy	1	153	1	3	2	156
14	Iraq	-	-	2	88	2	88
15	Saudi Arabia	1	15	1	3	2	18
16	Malaysia	-	-	2	13	2	13
17	Canada	-	-	2	12	2	12
18	United Arab Emirates	-	-	2	1	2	1
19	Viet Nam	-	-	1	85	1	85

20	India	1	48	-	-	1	48
21	Croatia	-	-	1	23	1	23
22	Germany	-	-	1	20	1	20
23	Poland	-	-	1	8	1	8
24	Algeria	-	-	1	6	1	6
25	Egypt	-	-	1	5	1	5
26	South Africa	-	-	1	5	1	5
27	Indonesia	-	-	1	3	1	3
28	Israel	-	-	1	3	1	3
29	Norway	-	-	1	3	1	3
30	Turkey	-	-	1	3	1	3
31	Brazil	-	-	1	2	1	2
32	Iceland	-	-	1	2	1	2
33	Ireland	-	-	1	1	1	1
34	Finland	-	-	1	0	1	0

Abbreviations: R=Rank; TP =Total papers; TC = Total citations

The United States led in the number of published papers between 2014 and 2019 with three papers, followed by China, France, and the United Kingdom, each with two papers during the same period. In the 2020 to 2024 period, the United States maintained its lead with five papers, followed by South Korea and the United Kingdom, each with four papers. The table highlights the growing interest from institutions in South Korea, China, and Australia, as they each published four papers during the 2020 to 2024 period. Figure 7 visualises global collaboration patterns between countries based on shared references in publications. Larger nodes represent countries with higher publication volumes, such as the United States, United Kingdom, and China, highlighting their central roles in advancing GenAI in CRM. The clustering reveals strong regional collaborations, reflecting the geographic focus of research. For example, collaborations between the UK and Australia emphasise AI in construction management, while contributions from South Korea and China highlight technological innovation in Asia. These patterns suggest regional partnerships are driving thematic specialisation, influencing how GenAI technologies are tailored to geographic and industry needs.

3.8 Most Common Methods used to Identify the Benefits and Risks of GenAI for CRM

Research suggests that employing multiple methods for identifying benefits and risks in construction projects is more effective than relying on a single approach (Sharma and Gupta, 2019). However, using a single method for risk identification in construction research offers simplicity, consistency, efficiency, and a focused approach, leading to detailed insights and facilitating easier replication and analysis. This approach, however, may also introduce potential bias and the risk of overlooking critical factors (Adams, 2008). Table 9 outlines the frequency and percentage of articles using different numbers of methods for risk and benefit identification in construction research. It shows that 61.8% of the articles (34 articles) employed a single method, 30.9% (17 articles) used two methods, and 7.3% (4 articles) applied more than two methods. This indicates a strong preference for single method approaches in the research.

Table 9. Number of methods used to identify benefits and risks.

Benefits and risks identification methods	TP	%	R
The use of single method	34	61.8%	1
The use of two methods	17	30.9%	2
The use of more than two methods	4	7.3%	3

Abbreviations: TP =Total papers; % = Percentage; R =Rank

Risk and benefit identification is a critical component of risk management across various sectors. The methods can be categorised as either survey-based (e.g., checklists, matrices, interviews) or analytical search-based (e.g., fault tree analysis, Ishikawa diagrams) (Spodakh, 2021). A comprehensive literature review is often a foundational element in research studies, providing background information, establishing relevance, and guiding the research process (Parajuli, 2020). Furthermore, literature reviews enable researchers to gather information from a broad range of studies to identify potential benefits and risks based on prior research findings (Al-Mhdawi et al., 2024).

As shown in Table 10, the literature review was the most widely used method for benefits and risks identification, with 34.6% of the studies applying this method. GenAI model training and testing was the second most popular method, used in 27.2% of the selected articles. This approach involved training a GenAI model to assess its performance and efficiency, then analysing the results to determine whether the model enhanced the risk management process and to identify potential risks and challenges. Expert interviews were the third most commonly used method, employed in 13.6% of the selected studies. Interviews provided valuable insights into the potential benefits and risks of GenAI in CRM from experienced professionals in the field. However, these methods tend to be more time-consuming and resource-intensive compared to questionnaire surveys or literature reviews (Chahrour et al., 2021).

As shown in Figure 7, questionnaire surveys and case studies were used with similar frequency to identify the benefits and risks of GenAI in CRM, with percentages of 11.1% and 9.9%, respectively. Questionnaire surveys face challenges such as the potential for misunderstanding and the need for clear, unambiguous questions. Poorly designed surveys can discourage participation and raise ethical concerns (Mayer and Wellstead, 2018). Meanwhile, case studies are notable for their limitations in generalisability and challenges like low motivation for participation and the limited impact of technology (Bavdaz et al., 2020).

Finally, focus group sessions and Twitter data analysis were found to be the least commonly used methods for benefits and risks identification. The low usage of focus groups can be attributed to the difficulty in organising and coordinating group discussions, especially when participants are in different geographic locations. Additionally, focus group sessions tend to be more time-consuming and resource-intensive compared to other methods (Masadeh, 2012). Twitter data analysis is also limited by several factors. First, the cost of accessing and processing data poses a significant barrier, as only a small proportion of Twitter's publicly available data is free (Valkanas et al., 2014). Second, data collection is constrained by privacy, policy, and marketing considerations, which can hinder effective use of the data. Furthermore, using keywords or hashtags to collect data may result in missing important sections of conversations (Moon et al., 2016).

Table 10. Methods for identifying GenAI benefits and risks

Benefits and risks identification method	TP	%	R
GenAI Model training and testing	22	27.2	2
Case study	8	9.9	5
Interviews	11	13.6	3
Questionnaire surveys	9	11.1	4
Literature review	28	34.6	1
Focus group session	2	2.5	6
Twitter data analysis	1	1.2	7

Abbreviations: R=Rank; TP =Total papers

3.9 Most Frequently Identified Categories of Benefits and Risks of GenAI for CRM

3.9.1 Classification of GenAI benefits

GenAI offers a wide range of key benefits to CRM, as identified in the 55 selected articles, with these benefits categorised into four main areas based on their sources: technical, technological, operational, and integration First and foremost, the technical benefits stand out as the most prominent category, with 36 mentions. As emphasised by Jallow et al. (2023), GenAI plays a critical role in enhancing core risk management processes. These processes include risk identification, where AI-powered tools provide earlier and more accurate detection of potential risks, risk prediction, where predictive analytics foresee potential issues based on historical and real-time data, and decision-making, where AI-driven simulations and recommendations aid in selecting optimal risk mitigation strategies. Moreover, the technology supports more effective risk response planning, allowing for better preparedness in managing unforeseen issues. This category demonstrates that GenAI's technical applications significantly strengthen a project's ability to handle risks from start to finish.

Following the technical benefits are the operational benefits, which rank second with 25 mentions. According to Erfani and Cui (2022), GenAI is transforming project management by offering deeper insights into scheduling, cost estimation, and quality control—all of which have a direct bearing on risk management. The ability to create more precise schedules and budgets reduces the likelihood of project delays and cost overruns, two of the most common risks in construction. Furthermore, by facilitating the identification and analysis of risks tied to these operational factors, GenAI helps ensure that projects adhere to planned timelines and budgets, ultimately enhancing project performance. Thus, the operational benefits of GenAI extend well beyond individual tasks, making it an invaluable tool for comprehensive risk management in construction projects. Technological benefits, which were mentioned 13 times, rank third in this analysis. As outlined by Pan and Zhang (2021), GenAI advances the technological aspects of risk management by automating repetitive tasks, reducing the potential for human errors, and improving cybersecurity. Automation of routine processes not only saves time but also minimises human involvement in error-prone tasks, thereby lowering the risk of costly mistakes. Additionally, GenAI's cybersecurity enhancements are crucial in today's digital construction landscape, where projects are increasingly vulnerable to cyber threats. By fortifying systems against these risks, GenAI helps protect sensitive project data and prevents potential disruptions caused by cyberattacks.

Finally, the integration benefits of GenAI, though less frequently mentioned (four times), offer unique opportunities for risk mitigation through the incorporation of advanced software systems. As highlighted by Hu and Castro (2019), GenAI's integration with Building Information Modeling (BIM) and blockchain technology opens new avenues for reducing construction risks. When integrated with BIM, GenAI helps anticipate design-related risks by creating more accurate, data-driven models. On the financial front, integrating GenAI with blockchain enhances transparency and security, reducing the risk of financial discrepancies and fraud. Although this category ranks last in terms of the frequency of mentions, the integration of GenAI with other innovative technologies presents promising possibilities for enhancing risk management practices in construction. Table 11 presents the categories of identified GenAI benefits, along with the total number of papers and their respective rankings. Figure 8 illustrates the distribution of articles exploring various categories of GenAI benefits.

Table 11. Total number of articles categorising GenAI benefits

Category	TP	R
Technical benefits	36	1
Technological benefits	13	3
Integration benefits	4	4
Operational benefits	25	2

TP =Total papers; R=Rank

3.9.2 Classification of GenAI risks

The analysed papers revealed nine categories of GenAI risks in CRM, grouped based on their sources, namely social, security, data, integration, performance, legal, resource, efficiency, and operational-related risks, as shown in Table 12. Social risks include factors like lack of awareness, trust, transparency, privacy, and stakeholder engagement, with cultural resistance further complicating the integration process, as noted by Pillai et al. (2020) and Regona et al. (2022). These social risks are ranked second, appearing 16 times across the reviewed articles, emphasising their significance in the successful and ethical implementation of GenAI. Security risks are another key area, as highlighted by Obiuto et al. (2024), who pointed out the dangers posed by data breaches, noncompliance with privacy protocols, and adversarial cyberattacks. These risks, although critical, rank seventh and are mentioned five times, indicating the need for proactive measures to ensure system integrity.

The most prominent category is data risks, ranking first due to its frequent mention in the literature. The quality, availability, and diversity of data are crucial for the effective functioning of GenAI models, as discussed by Holzmann and Lechiara (2022). Poor data quality can lead to incorrect predictions and decision-making, making data management a key factor in the successful application of GenAI in CRM. Integration risks, though less frequently discussed, still pose significant challenges. Singh and Adhikari (2023) highlighted the risk of interoperability issues when integrating GenAI with legacy systems, and Pillai and Matus

(2020) emphasised the need for professional management skills to ensure seamless integration with existing project management tools. These risks rank last, with only seven mentions, but remain critical for smooth GenAI integration. Performance risks, related to unclear responsibility and the selection of inappropriate machine learning algorithms, can lead to inaccurate analysis and flawed decision-making. Ensuring that AI models are fed with accurate data and choosing the right algorithms are essential to maintaining high performance. Legal risks, as noted by Yigitcanlar et al. (2022), include privacy breaches, failures in data retention, and issues with data anonymisation, which can have severe financial and reputational impacts. These risks are particularly dangerous due to their potential to lead to project failure if not addressed, making them one of the most significant threats to successful CRM implementation. Resource risks involve the lack of necessary equipment, such as sensors, drones, and cloud servers, as well as internet connectivity issues, and rank third, with 14 mentions in the selected articles. Without adequate resources, the effective application of GenAI in CRM could be compromised. Efficiency risks, related to the GenAI model's ability to accurately identify, assess, and respond to risks, rank fourth and were mentioned 13 times. Chenya et al. (2022) demonstrated that inaccurate risk identification and flawed decision-making could result from inefficiencies in AI models, further complicating risk management.

Lastly, operational risks, which focuses on the impact of GenAI the core operational aspects of project management, including time management, cost control, quality assurance, and stakeholder coordination. Barcaui and Monat (2023) pointed out that incorrect decisions or responses from GenAI can negatively affect these operational domains, leading to delays, budget overruns, or diminished quality standards. These operational risks were mentioned 11 times in the reviewed articles and rank fifth in importance. Specific benefits of GenAI, such as improved risk prediction and decision-making, can mitigate risks like operational inefficiencies and data-related issues but may also exacerbate others, including increased reliance on data quality and ethical concerns tied to AI-driven decisions. Assessing risks based on their potential impact and likelihood may provide more effective guidance in risk assessment than relying solely on their frequency in the literature. For instance, data risks, though frequent, might be mitigated through robust governance, while high-impact legal risks, such as privacy breaches, demand immediate attention. A balanced approach aligning benefits with targeted risk mitigation strategies is essential for responsibly integrating GenAI in CRM. Figure 9 presents the distribution of articles examining different categories of GenAI risks, showcasing the key areas of risks.

Table 12. Total number of articles categorising GenAI risks

Category	TP	R
Social risks	16	2
Security risks	9	7
Data risks	20	1
Integration risks	5	8
Performance risks	11	5
Legal risks	10	6
Resources risks	14	3
Efficiency risks	13	4
Risks of impacting other knowledge area	11	5

Abbreviations: TP =Total papers; R=Rank

4. Conclusion

Our findings highlight several important trends and considerations regarding the use of GenAI in CRM. Firstly, the increasing number of publications, particularly between 2020 and 2024, indicates a growing recognition of the importance of GenAI in CRM. This trend suggests that GenAI is likely to play a crucial role in the future of construction engineering and management practices. Secondly, the involvement of a wide range of countries and institutions demonstrates that the research landscape on GenAI in CRM is globally distributed. This highlights the strong international interest in the topic, offering opportunities for broader collaboration and cross-cultural learning. Thirdly, the use of multiple research methods, such as literature reviews, expert interviews, case studies, and model testing, to identify key benefits and risks of GenAI could significantly enhance the robustness of the findings. However, practical constraints such as time, cost, and resource availability often influence the selection of methodologies. While multi-method approaches have the potential to provide a more thorough and comprehensive exploration of the benefits and risks, researchers must carefully balance resource limitations with methodological rigour. Furthermore, categorising the benefits of GenAI into technical, operational, technological, and integration aspects demonstrates the diverse improvements GenAI can bring to CRM. At the same time, the identification of various risk categories, particularly those related to data and social issues, underscores the need for effective strategies to address and mitigate these risks as GenAI becomes more integrated into construction practices. Additionally, it is imperative to improve the understanding and perception of GenAI's potential in CRM to ensure its seamless integration into key risk management processes. Lastly, it is important to develop comprehensive risk management models that can effectively analyse, respond to, monitor, control, and communicate identified risks. Such models should also be capable of leveraging the opportunities that arise from the adoption of GenAI in CRM.

Theoretical and Practical Implication

This bibliometric research stands out as comprehensive analysis systematically mapping the dual impact of GenAI on CRM, addressing gaps left by prior studies that often focused on isolated applications. Through the categorisation of benefits and risks, the identification of emerging themes, and the mapping of global contributions. Its findings not only enhance theoretical understanding but also equip professionals with actionable insights to integrate GenAI responsibly into CRM practices, reinforcing its value to both academic and professional communities. Academics can identify key works and scholars in the field. This data is useful for understanding research gaps, guiding new research directions, and fostering collaborations between authors and organisations. The analysis of the most contributing authors, institutions, and countries also highlights leading experts and subjects of interest for these institutions and authors, promoting networking and partnerships that can drive further advancements in the field.

Additionally, the identification of commonly used methodologies offers a valuable reference for researchers seeking to adopt or refine techniques for evaluating the benefits and risks of GenAI in CRM. On the practical side, many of the implications related to identifying the benefits and risks categories of GenAI for CRM can help stakeholders in the construction industry—such as project managers, engineers, and risk management professionals—make informed decisions when integrating GenAI technologies into their workflows. Furthermore, the categorisation of GenAI risks in CRM is provided to assist practitioners. This categorisation supports subsequent stages of the risk management process, including risk analysis, risk evaluation, response planning, and monitoring and control.

The bibliometric analysis also reveals not only potential advantages, such as improved risk prediction and mitigation strategies, but also associated risks, such as ethical concerns and data security issues. Understanding these aspects can help practitioners balance innovation with caution, ensuring that GenAI is implemented in a way that maximises benefits while minimizing potential downsides.

Future Research Directions

Conducting interviews with industry experts to compare the benefits and risks identified in this study with real-world insights will enhance the depth of understanding. This expert-driven approach will not only validate the findings but may also uncover additional insights, expanding the scope of both opportunities and threats posed by GenAI in CRM. Moreover, future research should aim to quantify risks by considering factors such as their impact, likelihood, organisational adaptability, and awareness of AI technologies. A quantitative assessment of these risks will provide a clearer picture of their significance, enabling organisations to better anticipate and mitigate potential challenges posed by GenAI. Finally, research should focus on developing an optimisation model for risk-response strategies, facilitating the selection of appropriate responses to address identified risks while capitalizing on emerging opportunities. This will provide organisations with practical tools for enhancing their CRM processes in the context of GenAI.

Research Limitation

Despite the comprehensive analysis conducted in this study, several limitations should be acknowledged. First, the scope of the research was limited to peer-reviewed articles published between 2014 and 2024, which may have excluded relevant studies published outside this period or in non-peer-reviewed sources. Second, the bibliometric analysis focused on a specific set of keywords, which could have resulted in the exclusion of relevant articles that used different terminology for GenAI or were categorised under other related fields. Third, while the study categorised the benefits and risks associated with GenAI in CRM, it did not include expert interviews to validate these findings. Although this may limit the depth of understanding, the study still provides a solid foundation based on the existing literature. Incorporating expert perspectives in future research could further enrich the insights and potentially reveal additional categories of risks and benefits.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Data availability statement

All data generated or analysed during the study are included in the paper.

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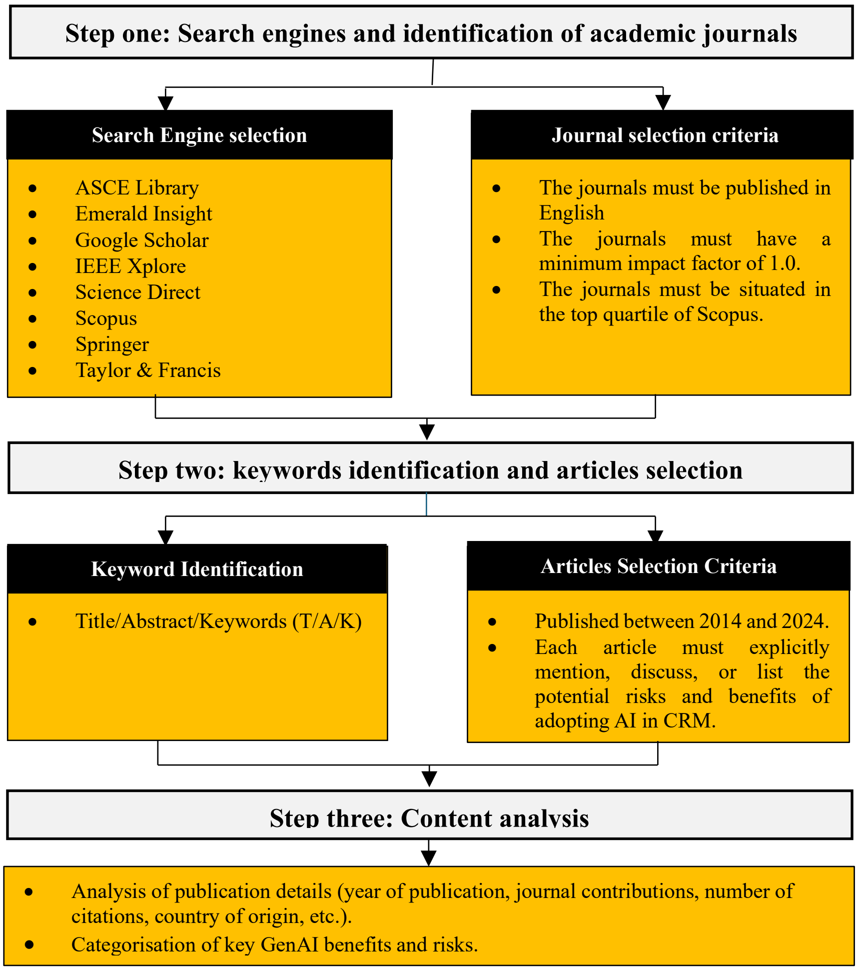

Figure 1. Adopted research methodology

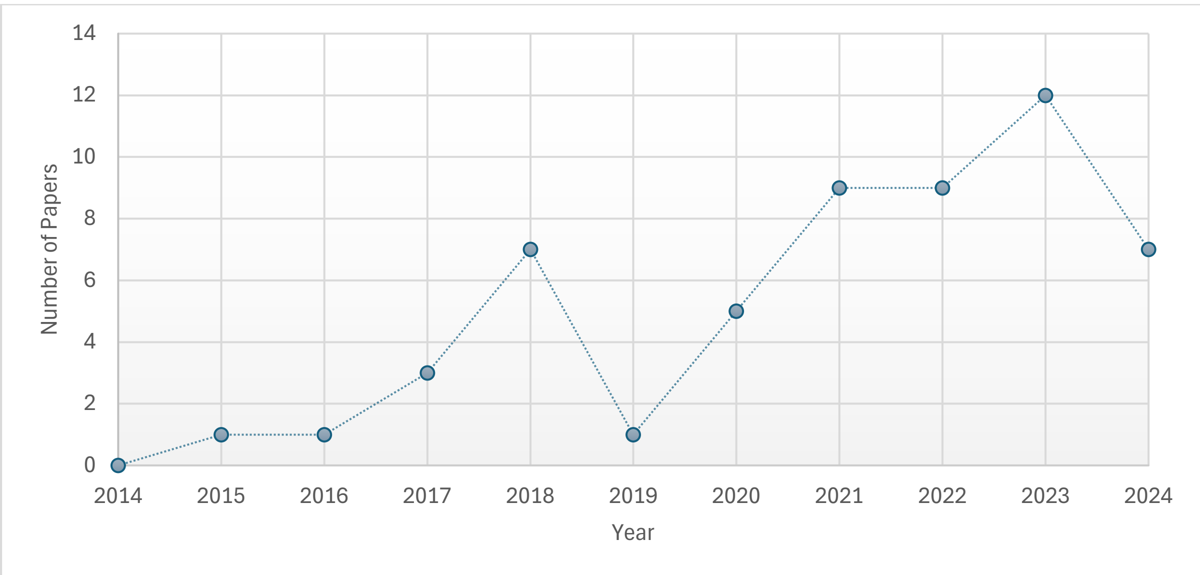

Figure 2. Publication trends from 2014 to 2024

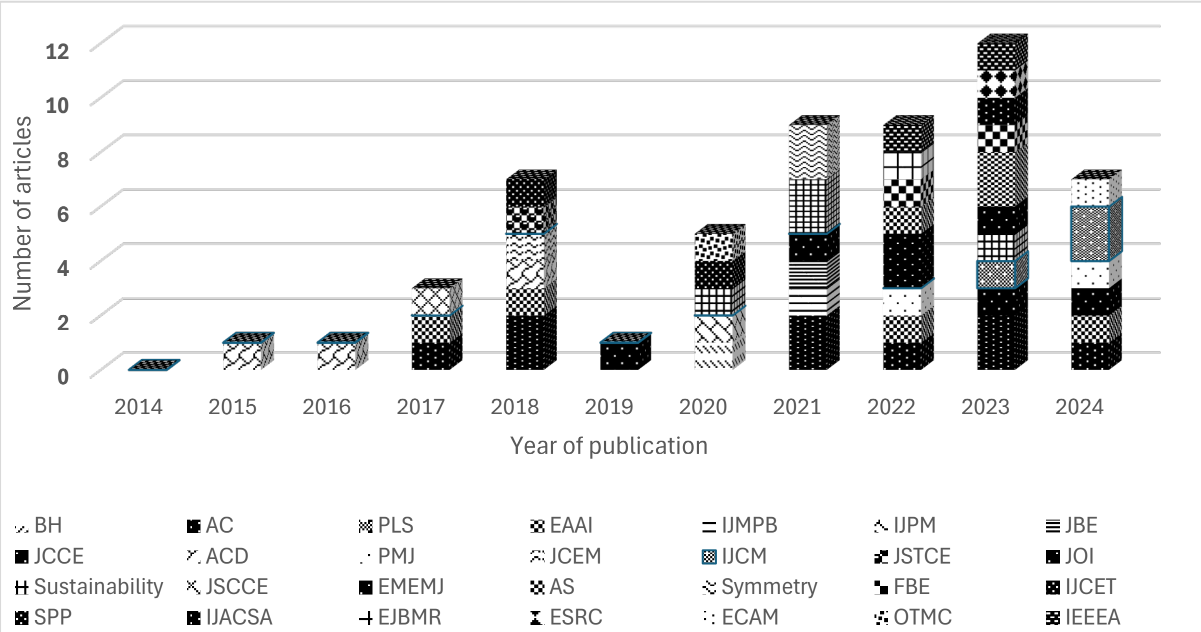

Figure 3. Journal contribution with respect to year of publication

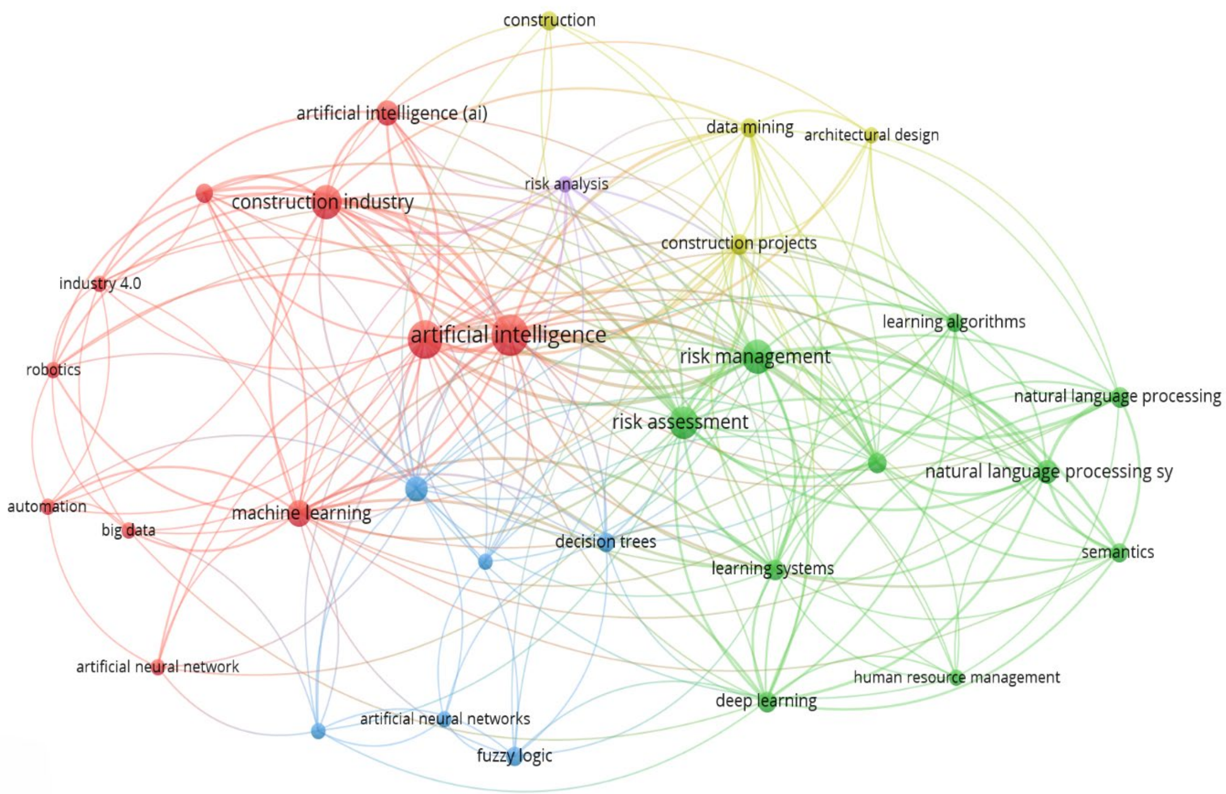

Figure 4. Keyword occurrence and Co-occurrence of author keywords

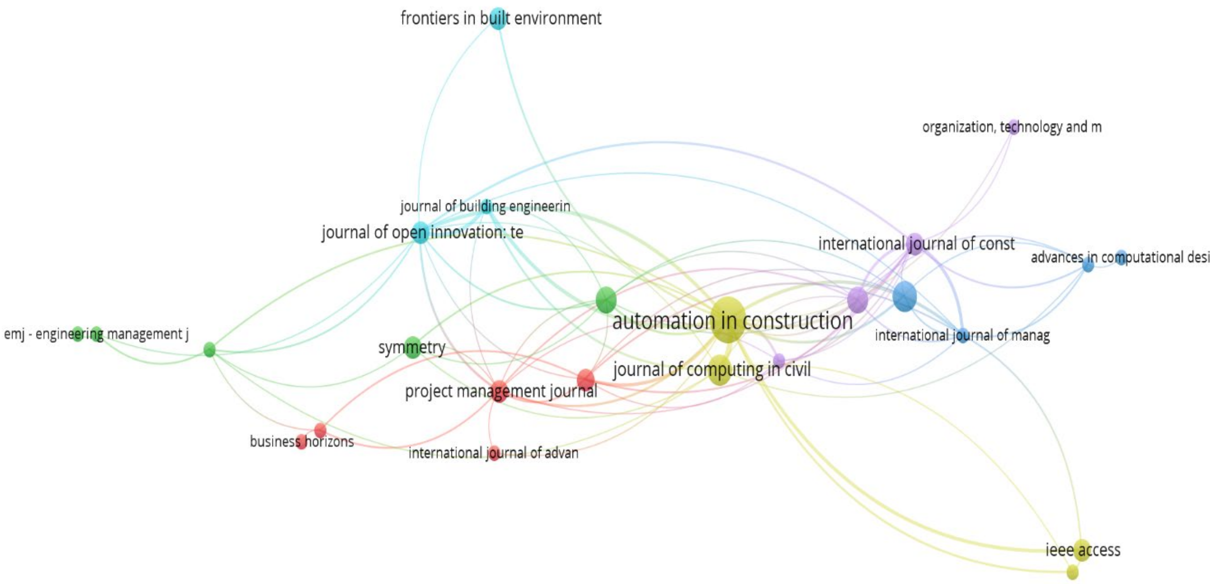

Figure 5. Bibliographic coupling of analysed articles

Figure 6. Density visualisation of leading contributors (2014–2024)

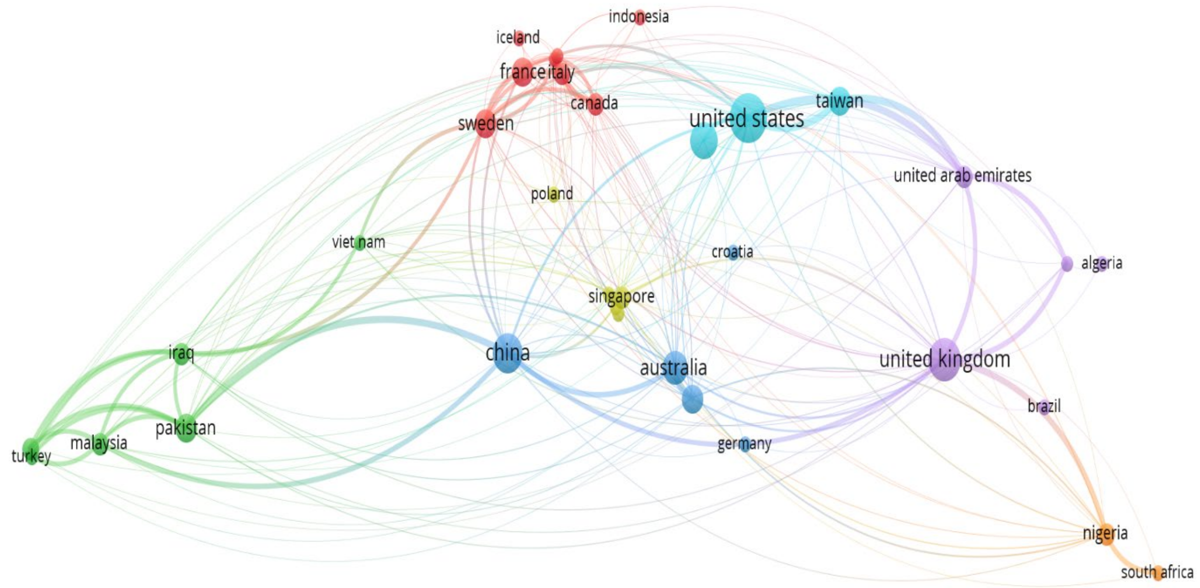

Figure 7. Bibliographic coupling of countries publishing relevant articles

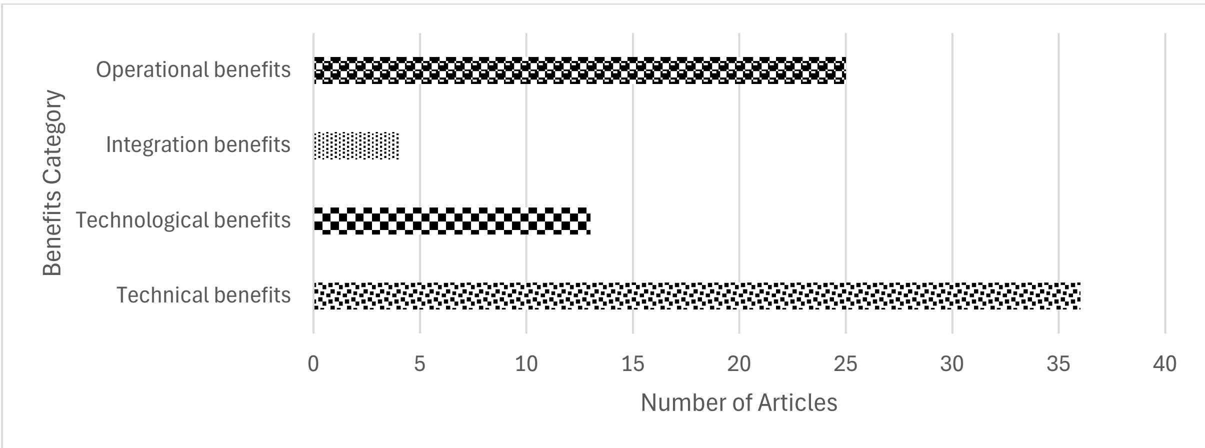

Figure 8. Number of articles exploring categories of GenAI benefits