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A meta-synthesis of the strategic advantages of AI–BIM integration in AEC projects

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This study explores the transformative potential of integrating artificial intelligence (AI) with building information modelling (BIM) in architecture, engineering, and construction (AEC) projects, identifying strategic benefits in productivity, innovation, and sustainability while addressing research gaps through a comprehensive framework to guide professionals and policymakers in optimising outcomes, enhancing decision making, and promoting sustainability. Using a meta-synthesis approach and NVivo-based pattern analysis, data from 65 research papers was synthesised, employing temporal and co-occurrence analyses to uncover AI-BIM benefits across seven domains – automation, decision making, design, knowledge, sustainability, collaboration, and cost optimisation – offering a systemic perspective beyond prior technical studies. Findings show AI-BIM enhances AEC projects, with superior design and productivity gains peaking at 15 codes in 2024 due to generative design, a strong synergy between automation and design (52 co-occurrences) and knowledge (57 co-occurrences) driving innovation, cost efficiency underexplored at four codes in 2023, and collaboration peaking at 13 codes in 2024. This pioneering framework, built via meta-synthesis and co-occurrence analysis, quantifies benefits like design gains, emphasises systemic interactions, and provides practical guidance for stakeholders to boost innovation and sustainability, extending prior work and setting the stage for future research into precise AI-BIM impacts.

Keywords: building information modeling (BIM), artificial intelligence (AI), integration, advantages, meta-synthesis, AEC projects



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INTRODUCTION

Amid the growing complexities of architecture, engineering, and construction (AEC) projects – marked by escalating costs, tight schedules, and stringent sustainability demands – two pioneering technologies – artificial intelligence (AI) and building information modelling (BIM) – have emerged as critical drivers of innovation and efficiency (Saghatforoush *et al* 2023). With BIM providing a structured digital platform for project data, and AI offering advanced capabilities to analyse vast datasets, predict outcomes, and optimise processes, their integration holds the potential to revolutionise construction workflows, particularly in addressing challenges like inefficient resource use and delayed decision making (Jadidoleslami *et al* 2025). Yet, a pressing question remains: does this integration truly deliver strategic advantages capable of transforming AEC projects amidst these pressures? This research is driven by this uncertainty, aiming to identify and articulate the specific benefits of AI-BIM integration to guide the industry's digital evolution.

The fusion of AI and BIM promises enhanced process automation, resource optimisation, and sustainability, but the lack of a comprehensive understanding of their necessity and benefits in AEC projects underscores a critical knowledge gap (Sacks *et al* 2022). The urgency of this study arises from rapid technological advancements and the industry's pressing need to adopt digital solutions, as traditional BIM, while improving transparency and collaboration, struggles with complex data analysis and automation (Sacks *et al* 2020, Darko *et al* 2020). AI, with its prowess in forecasting and optimisation,

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complements these limitations (Hanafy 2023, Pan & Zhang 2021), but the absence of integrated frameworks hinders its full potential. Recent evidence highlights the critical role of scalability, technology adoption, and sustainability in AEC success (Cotella 2023, Yevu *et al* 2025, Sacks *et al* 2022), areas where AI-BIM integration could provide solutions, as suggested by early findings on environmental impact reduction (Gao *et al* 2024). However, the literature reveals a significant shortfall: existing studies rarely offer a holistic conceptual framework to evaluate these advantages, focusing instead on isolated aspects like technical implementation or specific case studies, leaving the broader strategic benefits underexplored.

This research specifically targets the question of what the primary advantages of integrating AI and BIM are in the construction industry, and how these advantages can inform practical strategies to drive innovation and sustainability in AEC projects. Answering these questions is essential to empower policymakers, practitioners, and researchers with evidence-based insights to navigate the digital transformation of AEC projects. The structure of this article is designed to address these inquiries: the second section outlines the literature screening process; the third section details the methodology, utilising the meta-synthesis and pattern analysis with NVivo software to synthesime diverse studies; the fourth section presents findings, framing the strategic advantages within a conceptual framework; the fifth section discusses these results, comparing them with prior research and analysing their implications; and the sixth section concludes by summarising the outcomes, offering recommendations, and highlighting practical applications. This structured approach bridges the identified gap, providing a robust rationale for investigating AI-BIM integration as a cornerstone for future AEC advancements.

LITERATURE SCREENING

The integration of BIM and AI represents an innovative synergy, opening new horizons in the construction industry and project management. BIM is defined as a parametric, object-oriented digital representation of the physical and functional characteristics of a built asset that serves as a shared knowledge resource for decision making throughout its life cycle (ISO 19650). AI, on the other hand, refers to the capability of computational systems to perform tasks that typically require human intelligence, including machine learning, deep learning, natural language processing, and generative models, particularly when applied to the analysis, prediction, and optimisation of BIM data. Unlike BIM, which serves as a specialised, engineering-focused language, AI's linguistic and conceptual flexibility enables broader interaction beyond technical limitations (Saka *et al* 2024, Jadidoleslami & Azizi 2022, Jadidoleslami *et al* 2025a). AI's capacity to process and analyse vast datasets, from complex blueprints to environmental and historical data, significantly enhances decision-making accuracy and speed (Soori *et al* 2026). Such integration not only reduces human errors but also boosts sustainability and efficiency in projects by anticipating challenges and optimising resources (Pan & Zhang 2021). Moreover, AI can uncover hidden patterns within BIM datasets (Sacks *et al* 2020), fostering the creation of tailored solutions.

Among the studies addressing this domain, Pan and Zhang (2023) emphasise that BIM serves as a digital backbone of the AEC industry, with AI enhancing this foundation by processing vast and complex datasets. This work highlights the convergence of these technologies to address the complexities and uncertainties of modern construction, focusing on analytical forecasting and real-time monitoring, yet it lacks a comprehensive framework for the advantages of this integration. Similarly, Zhang *et al* (2022) explore deep digitalisation enabled by BIM and AI, arguing that their synergy advances sustainable construction and smart city development through optimised design decisions and reduced environmental impacts. However, this study remains case-specific, offering limited generalisable insights. Du (2021) underscore the integration's role in automating construction management tasks like cost estimation and quality control, but it provides minimal analysis of long-term benefits or a unified framework. Other investigations, such as those on deep learning models (Topuz & Alp 2023, Zabin *et al* 2022) and generative AI in conceptual design (Hanafy 2023, Taiwo *et al* 2025, Zheng 2025), focus narrowly on technical advancements, often overlooking broader advantages and long-term impacts.

A review of existing literature reveals a predominant focus on specific aspects – project management, sustainability, and data processing – generating valuable but fragmented knowledge. These studies collectively establish that BIM provides structured data for AI to analyse, improving decision making, resource optimisation, and design innovation, as seen in the pattern-recognition capabilities noted by Sacks *et al* (2020) and the sustainability gains highlighted by Zhang *et al* (2022). However, they fall short in synthesising these findings into a cohesive conceptual framework, leaving gaps in understanding the holistic advantages – such as enhanced productivity, cost reduction, and stakeholder collaboration – and their interrelationships. This study extends prior fragmented reviews by employing a meta-synthesis approach (Noblit & Hare 1988, Lachal *et al* 2017) to aggregate and interpret these insights, thereby generating a unified conceptual framework that not only identifies the key benefits but also models their interrelationships and synergies – directly addressing the limitations identified in earlier technical and case-specific studies. As explicitly advocated in the meta-synthesis literature, this interpretive translation of findings across multiple studies enables the construction of higher-order concepts and relational patterns that single studies or conventional systematic reviews cannot achieve (Zimmer 2006, Beck 2002).

RESEARCH METHODOLOGY

Aligned with the research objective of identifying the strategic advantages of integrating AI and BIM, this study employs the meta-synthesis approach to address this target. The remarkable growth of knowledge and expanding accessibility of scientific resources have enriched the research literature across various domains. However, reviewing and synthesising all relevant studies requires a scientific and systematic approach. Consequently, structured methods for identifying, summarising, and extracting concepts from existing theoretical foundations have increasingly been developed. Meta-synthesis, which follows pre-defined stages to integrate findings from prior studies and offers innovative analysis to generate new knowledge, proves valuable in this context.

The meta-synthesis approach focuses on qualitative studies, which may not necessarily encompass extensive theoretical bases, and instead of providing a mere summary of findings, it creates an

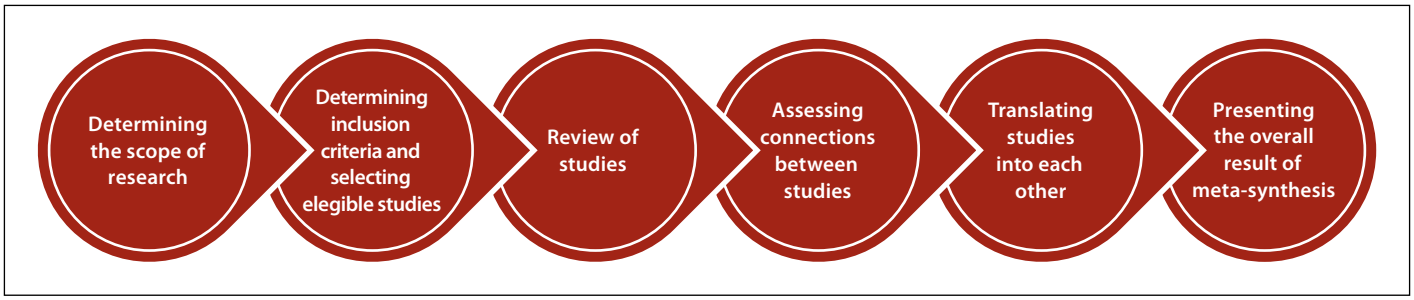


Figure 1 Steps of the meta-synthesis method (Noblit & Hare 1988)

interpretive synthesis (Zimmer 2006). The interpretive perspective inherent in the meta-synthesis technique is a distinctive feature, as this interpretation does not exist in any single research report but is inferred from them collectively. By integrating multiple studies to produce comprehensive and interpretive findings, the meta-synthesis emphasises qualitative research and relies on the researcher's deep understanding (Beck 2002).

There remains no universal consensus on many stages and models of the meta-synthesis technique. Although synthesising and reviewing qualitative studies have been common in the past, this process has often lacked a systematic and structured approach. However, Noblit and Hare (1988) developed a specific framework known as meta-ethnography for conducting the meta-synthesis, which has since been utilised in numerous studies. In this model, after outlining criteria for comparing qualitative research projects, the authors define methods that can be applied to create a more compelling synthesis of accumulated research. This framework is among the most widely used meta-synthesis models, comprising six main stages (Lachal *et al* 2017), and shares similarities with the principles of systematic reviews of quantitative studies in many respects. Nevertheless, differences exist between these approaches in data collection, result extraction, and interpretation of findings, which will be explored in detail in the following sections. The stages of this method are illustrated in Figure 1.

The meta-synthesis (systematic literature review) steps

Step 1: Determining the scope of research

This phase involves defining the research objective through the research question and theoretical framework. The scope of study must be broad enough to fully encompass the dimensions of phenomenon under investigation while remaining sufficiently specific. The chosen topic for meta-synthesis should hold sufficient scientific merit and offer potential applications for advancing knowledge, theory development, or performance improvement. Additionally, the researcher must have a genuine interest in the topic and possess adequate knowledge and experience in the area.

As previously noted, this study seeks to address the question of what the strategic advantages of integrating AI and BIM are in the construction industry.

Step 2: Determining inclusion criteria and selecting eligible studies

In this phase, researchers establish diverse inclusion and exclusion criteria for studies based on research domain and topic. Overall, it is essential that all studies examine a common phenomenon. Opinions on the number of eligible studies vary widely, with significant differences. However, it is generally recommended that studies be selected for their diversity and quantity to ensure adequate coverage of demographic factors influencing results, with inclusion continuing until theoretical saturation of information is achieved, particularly for qualitative research strategies. Experienced researchers may reach conclusive findings with fewer studies. Schreiber *et al* (1997) argue that the number of studies to include in the synthesis depends on the research topic and the researcher's objectives. Furthermore, the sample size is contingent on the complexity of the posed question and depth and breadth of existing research (Corbin & Strauss 2014).

Following meta-synthesis guidelines (Beck 2002), a search in ScienceDirect, Scopus, WoS and Google Scholar used the query *TOPIC ("Building Information Modelling" OR "BIM") AND TOPIC ("Artificial Intelligence" OR "AI")* for English-language, peer-reviewed journal/conference articles (2015–2025). The terms "Artificial Intelligence" OR "AI" were selected because these are the standard indexing keywords used by the selected databases and because the large majority of studies applying machine learning, deep learning, generative AI, or large language models in a BIM context explicitly reference "AI" in the title, abstract, or keywords. Consequently, papers focused on these sub-components were captured whenever they addressed BIM integration. Narrower terms (e.g. "machine learning", "generative AI") were not added separately to maintain search reproducibility and avoid redundancy. While this approach minimises omission bias, a small risk remains that highly specialised papers referring only to specific algorithms without using the term "AI" might have been excluded; this limitation is acknowledged in the discussion section of this paper.

From 1 025 initial results, 133 remained after title/abstract screening for AI-BIM integration, and 122 were included after full-text review for qualitative/mixed-method studies addressing BIM dimensions. Non-English, quantitative-only theses, reports, or books were excluded. Duplicates were removed using EndNote. Articles were manually coded by mapping content to BIM dimensions (3D: geometric modelling through 10D: industrialised construction; (Jadidoleslami & Saghatforoush 2026)) as well as to the specific advantages of integrating AI and BIM, allowing multiple counting. These dimensions follow the extended framework now widely adopted in the literature (Succar *et al* 2012, Jadidoleslami & Saghatforoush 2026), where each dimension represents a distinct layer of information (e.g. time in 4D, cost in 5D, sustainability in 6D) rather than maturity levels or standalone benefits. According to Figure 2, articles that did not meet the above criteria were screened and eliminated in several stages. NVivo was used for thematic analysis of full texts from 122 articles to identify and categoriwe the techniques of applying AI in BIM. An open coding scheme was applied by two researchers, with themes categorised

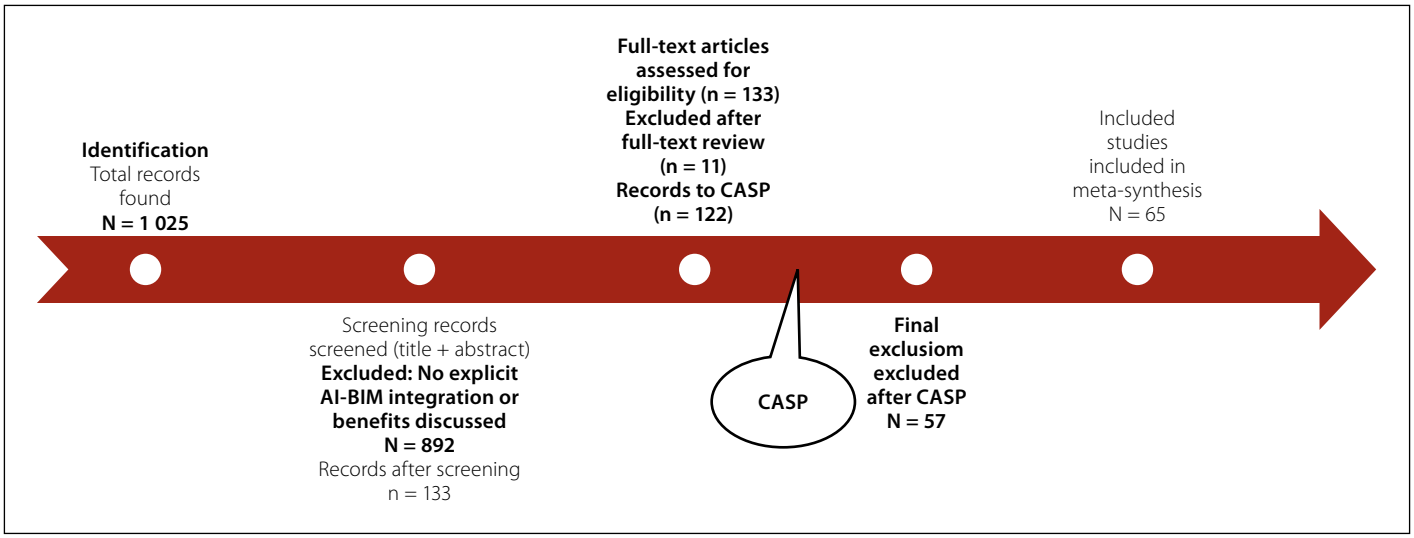


Figure 2 PRISMA flow diagram of the study selection process

Table 1 Inclusion and exclusion criteria

	Exclusion criteria	Inclusion criteria
Relevance	Studies that explicitly investigate the integration of AI and BIM or report empirical/theoretical benefits or outcomes of such integration (assessed at title, abstract, and full-text stages)	AI–BIM integration focus
Publication time	–	Unrestricted
Research method	Quantitative	Qualitative, quantitative-qualitative (mixed methods)
Type of studies	Theses, reports, books	Journals and conferences
Scope	Articles unrelated to the field of construction	Construction
Article Language	Non-English	English

iteratively. Inter-coder reliability ensured consistency. The criteria for accepting or rejecting articles in this study are outlined in Table 1.

A critical acceptance criterion applied at both the title/abstract screening and full-text review stages was that each article must explicitly address the integration of AI and BIM or report benefits arising from their combined use (see Figure 2 for the corresponding screening stages). Figure 2 presents the PRISMA flow diagram illustrating how the inclusion and exclusion criteria (including the explicit requirement for AI–BIM integration focus) were applied at each stage to ensure that only studies aligned with the research objective — identifying the strategic advantages of AI–BIM integration — were retained.

According to Figure 2, articles that did not meet the above criteria were screened and eliminated in several stages.

Step 3: Review of studies

In this stage, each study is meticulously reviewed multiple times, scored based on its alignment with inclusion criteria for the synthesis pool, and evaluated for scientific adequacy. Dixon-Woods *et al* (2007) recommend that researchers employ critical appraisal criteria at this stage and not limit this process to the previous phases, as critical evaluation of initial studies is a dynamic and ongoing process that should persist throughout subsequent stages.

In this evaluation, each article was assessed using the Critical Appraisal Skills Programme (CASP) qualitative checklist (CASP 2018). The following ten questions were applied:

- Was there a clear statement of the aims of the research?
- Is a qualitative methodology appropriate?
- Was the research design appropriate to address the aims?
- Was the recruitment strategy appropriate?
- Was the data collected in a way that addressed the research issue?
- Has the relationship between researcher and participants been adequately considered?
- Have ethical issues been taken into consideration?
- Was the data analysis sufficiently rigorous?
- Is there a clear statement of findings?
- How valuable is the research?

Each question was scored from 1 to 5, with a minimum total score of 31 required for inclusion. This quality threshold was applied after the initial inclusion/exclusion screening to ensure that only high-quality studies addressing AI–BIM integration contributed to the meta-synthesis. Following this assessment, 65 articles remained. Notably, although no time restrictions are applied in the inclusion criteria, the relevant studies for this research, after screening, fell within the timeframe from 2018 to the first quarter of 2025.

Step 4: Assessing connections between studies

In this phase, the researcher evaluates how studies relate to one another, examines their degree of homogeneity, and categorises them based on their characteristics. A summary table of the studies' information and features is presented, and extracted codes from each article are identified (see Table 2). Identical or conceptually similar codes are merged as needed to facilitate synthesis.

Step 5: Translating studies into each other

In meta-synthesis, "translation" refers to the abstract transformation of corresponding key concepts across different studies. After forming and refining clusters of similar metaphors, the aim is to develop descriptions of primary shared categories of the phenomenon under study.

Table 2 Extracted codes

Row	Advantages	Related research
1	Enhanced automation and efficiency, improved problem-solving capabilities, visualisation and research insights, scientometric tools, support for optimisation and simulation, global research momentum, better decisions, real-time decision support, knowledge discovery.	Darko *et al* 2020, Andritsou *et al* 2024, Choi *et al* 2024, Frías *et al* 2020, Liu & Jiang 2021, Mehraban *et al* 2024
2	Enhanced design and construction processes, improved project insights, real-time decision support, optimisation of resources, advancement of construction technology.	Sacks *et al* 2020, Morsi *et al* 2022, Mostafa *et al* 2023, Rane *et al* 2023, Rane 2023, Al-Muntaser & Ashur 2024
3	Explicit coding, recurring user input, subjective ratings to recommend BIM content to users, achieve significant savings in time spent on typical BIM workflows, facilitate organising, searching, loading BIM content (with cloud repositories, digital libraries, add-on user interfaces, and search engines), mine big data analytics of BIM objects from the content used in historical BIM models, measuring the statistical probability for co-occurrence and associations between BIM objects based on their technical precedents in BIM views (e.g. sections, details).	Abdirad & Mathur 2021, Bienvenido-Huertas *et al* 2020, Ceccarelli *et al* 2023, Croce *et al* 2023, Cotella 2023
4	Improved productivity, optimised decision making, enhanced efficiency across life cycle, algorithm-specific strengths, and potential for mitigation strategies.	An *et al* 2021, Mostafa *et al* 2023, Baduge *et al* 2022, Omotayo *et al* 2024, Khan *et al* 2024
5	Future-oriented insights, optimisation of design and construction, improved risk management, enhanced predictive capabilities, automation of BIM processes, future-oriented insights, optimisation of design and construction, improved risk management, cost reduction over time, enhanced collaboration, sustainability improvements, and adaptability to complex projects.	Pan & Zhang 2021, Rangasamy & Yang 2024, Rane *et al* 2023, Ploszaj-Mazurek & Rynska 2024, Andritsou *et al* 2024, Sampaio *et al* 2022, Saleh *et al* 2024
6	Real-time data management, ease of use for novices, high interoperability, wide range of data access, support for users with disabilities, automated data retrieval, remote interaction capability	Elghaish *et al* 2022, Saleh *et al* 2024, Ploszaj-Mazurek & Rynska 2024, Al-Muntaser & Ashur 2024, Abdirad & Mathur 2021, Maureira *et al* 2021, Darko *et al* 2020, Xiang *et al* 2021
7	Collaboration enhancement, robustness and performance, future potential for innovation, better decision making, increased productivity, improved safety outcomes, enhanced project efficiency.	Emaminejad & Akhavian 2022, Maureira *et al* 2021, Mehraban *et al* 2024, Rane *et al* 2023, Al-Muntaser & Ashur 2024
8	Scalable access and flexibility, improved design quality, future paradigm shift, knowledge capture and reuse, enhanced decision making, automated design support, real-time multidisciplinary collaboration.	Sacks *et al* 2022, Sacks *et al* 2020, Sresakoolchai & Kaewunruen 2023, Carneiro *et al* 2018, Baduge *et al* 2022, Andritsou *et al* 2023, Andritsou *et al* 2024
9	Knowledge discovery, optimised project outcomes, informatisation and intelligence, automatic modelling capabilities, enhanced sustainable development, improved data management, and automation across life cycle.	Zhang *et al* 2022, Rane 2023, Abdirad & Mathur 2021, Almagboul *et al* 2021, Andritsou *et al* 2023, Bao & Cheng 2022, Yang & Xia 2023, Elghaish *et al* 2022, Pan & Zhang 2023
10	Cross-disciplinary applications, improved accuracy of parametric features, handling large-scale data, innovation in BIM-AI strategies, support for conservation, enhanced scene insight, automation of HBIM modelling.	Cotella 2023, Urbieta *et al* 2023, Ploszaj-Mazurek & Rynska 2024, Bienvenido-Huertas *et al* 2020, Langenhan *et al* 2023, Li *et al* 2024
11	Support for digital transformation, inclusivity for diverse users, future research opportunities, potential productivity gains, support for project management, real-time BIM data access, enhanced human-computer interaction.	Saka *et al* 2023, Xiang *et al* 2021, Urbieta *et al* 2023, Sun & Kim 2022, Saleh *et al* 2024, Alavi *et al* 2024, Almagboul *et al* 2021, Hsieh *et al* 2024, Musella *et al* 2019, Sresakoolchai & Kaewunruen 2021
12	Scalability for large projects, real-time decision support, sustainability benefits, post-implementation insights, automation of implementation tasks, improved material management, enhanced planning with BIM.	Balogun *et al* 2024, Yang & Xia 2023, Alavi *et al* 2024, Elghaish *et al* 2022, Vega-Torres *et al* 2024, Du *et al* 2024
13	Mitigation of human error, empowerment through automation, support for ethical innovation, transparency potential, enhanced project quality, increased productivity, improved safety outcomes.	Liang *et al* 2024, Yönder 2023, Sun & Kim 2022, He *et al* 2025, Zhang *et al* 2022, Urbieta *et al* 2023, Mostafa *et al* 2023
14	Sustainability through optimisation, real-time decision support, historical progress insights, automation of BIM processes, predictive maintenance capabilities, improved communication efficiency, enhanced security monitoring.	Mai *et al* 2024, Yang *et al* 2020, Yang & Xia 2023, Xing 2024, Alavi *et al* 2024, He *et al* 2025
15	Sustainability benefits, cost and time savings, future research potential, better information management, enhanced performance and productivity, quality improvement, improved design efficiency.	Rangasamy & Yang 2024, Mostafa *et al* 2023, Yönder 2023, Sun & Kim 2022
16	Cross-domain synergy, automation of facade analysis, growing research momentum, trend identification and insights, structural optimisation, improved environmental performance, enhanced facade design in BIM, creation of 3D BIM models.	Duran *et al* 2025, Ploszaj-Mazurek & Rynska 2024, Almagboul *et al* 2021, Andritsou *et al* 2024, Morsi *et al* 2022, Vega-Torres *et al* 2024
17	Versatility across BIM phases, support for productivity gains, framework for practical deployment, better information management, improved design generation, automation of BIM processes, enhanced BIM data querying.	Taiwo *et al* 2025, Yang *et al* 2020, Almagboul *et al* 2021, Yönder 2023
18	Future scalability with transfer learning, real-time emissions estimation, knowledge capture and model enhancement, optimised planning and decision making, advanced safety monitoring, improved quality control, enhanced productivity in BIM workflows.	Yevu *et al* 2025, Almagboul *et al* 2021, Andritsou *et al* 2024, Vega-Torres *et al* 2024, Ploszaj-Mazurek & Rynska 2024

Table 3 Advantages of BIM-AI integration

Code	Sub-codes
Automation and scalability benefits (ASB)	Enhanced automation and efficiency, support for optimisation and simulation, optimisation of resources, automation of BIM processes, automated data retrieval, automation of implementation tasks, automatic modelling capabilities, automation across life cycle, automation of HBIM modelling, automation of façade analysis, empowerment through automation, automation of design support, mitigation of human error, scalable access and flexibility, scalability for large projects, adaptability to complex projects, versatility across BIM phases, handling large-scale data, structural optimisation.
Enhanced decision making and insights (DMI)	Improved problem-solving capabilities, real-time decision support, better decisions, optimised decision making, enhanced decision making, post-implementation insights, optimised planning and decision making, enhanced predictive capabilities, visualisation and research insights, trend identification and insights, measuring statistical probability for co-occurrence, predictive maintenance capabilities, historical progress insights.
Superior design and productivity gains (DPG)	Enhanced design and construction processes, optimisation of design and construction, improved design quality, enhanced façade design in BIM, improved design generation, improved design efficiency, creation of 3D BIM models, improved productivity, increased productivity, potential productivity gains, enhanced performance and productivity, quality improvement, enhanced project quality, robustness and performance, support for productivity gains, enhanced efficiency across life cycle, improved material management, enhanced planning with BIM.
Knowledge advancement and innovation (KAI)	Knowledge discovery, real-time data management, wide range of data access, improved data management, better information management, knowledge capture and reuse, enhanced BIM data querying, mine big data analytics of BIM objects, future-oriented insights, future potential for innovation, future paradigm shift, future research opportunities, future research potential, growing research momentum, future scalability with transfer learning, innovation in BIM-AI strategies, support for ethical innovation, informatisation and intelligence, cross-domain synergy.
Sustainability and safety improvements (SSI)	Sustainability improvements, enhanced sustainable development, sustainability benefits, sustainability through optimisation, improved environmental performance, real-time emissions estimation, improved safety outcomes, improved risk management, advanced safety monitoring, enhanced security monitoring, mitigation of human error, support for conservation.
Collaboration and accessibility enhancements (CAE)	Enhanced collaboration, collaboration enhancement, real-time multidisciplinary collaboration, improved communication efficiency, enhanced human-computer interaction, high interoperability, ease of use for novices, support for users with disabilities, real-time BIM data access, inclusivity for diverse users, remote interaction capability, support for digital transformation.
Cost and resource efficiency (CRE)	Cost reduction over time, cost and time savings, achieve significant savings in time spent on typical BIM workflows, improved material management.

Descriptions provided in initial studies and direct quotes from these studies are used to elaborate each pattern and clarify concepts further. In this research, all extracted advantages from the studies are initially treated as codes. Then, considering the meaning of each code, they are categorised into similar concepts. This classification and coding are conducted using pattern analysis through the NVivo software. The categorisation of codes is presented in Table 3.

Step 6: Presenting the overall result of meta-synthesis

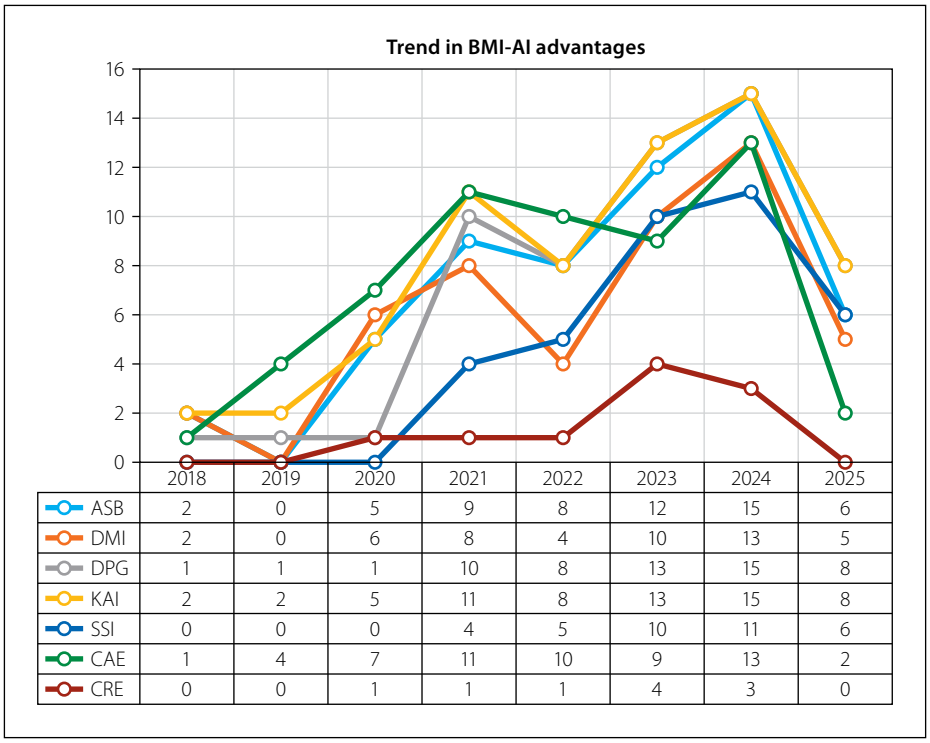
In this stage, the final meta-synthesis results are presented interpretively, extending beyond individual initial studies while encompassing them all, with the influence of each primary study discernible in the outcome. While the meta-synthesis directly identifies the advantages (the 'what'), the interpretive translation and relational analysis inherent in the method (Steps 5 and 6) also generate a conceptual framework that shows how these advantages can be harnessed. The resulting synergies and temporal patterns are therefore translated into stakeholder guidance in the discussion and conclusion sections. To interpret the results from the previous coding phase and identify which advantages are growing, which are diminishing, and which exhibit high co-occurrence – potentially serving as key areas for future research – two evaluation approaches of temporal trend analysis and co-occurrence analysis are employed. The temporal trend matrix is presented in Table 4.

For instance, in 2018, automation and scalability benefits (ASB) and knowledge advancement and innovation (KAI) each recorded two codes, while cost and resource efficiency (CRE) and sustainability and safety improvements (SSI) had no codes, indicating an early focus on foundational automation and knowledge capture. By 2024, the matrix exhibits the highest diversity, with 18 codes in KAI and 15 codes each in ASB and superior design and productivity gains (DPG), reflecting a broad adoption of AI-BIM integration across multiple dimensions. Based on the above matrix, the temporal trend chart is presented in Figure 3.

The temporal trend chart (Figure 3) illustrates the changes in code counts across seven categories of AI-BIM integration advantages— ASB, enhanced decision making and insights (DMI), DPG, KAI, SSI, collaboration and accessibility enhancements (CAE), and CRE – from 2018 to 2025. This visualisation reveals

Table 4 Temporal trend

	ASB	DMI	DPG	KAI	SSI	CAE	CRE
2018	2	2	1	2	0	1	0
2019	0	0	1	2	0	4	0
2020	5	6	1	5	0	7	1
2021	9	8	10	11	4	11	1
2022	8	4	8	8	5	10	1
2023	12	10	13	13	10	9	4
2024	15	13	15	15	11	13	3
2025	6	5	8	8	6	2	0



	2018	2019	2020	2021	2022	2023	2024	2025
ASB	2	0	5	9	8	12	15	6
DMI	2	0	6	8	4	10	13	5
DPG	1	1	1	10	8	13	15	8
KAI	2	2	5	11	8	13	15	8
SSI	0	0	0	4	5	10	11	6
CAE	1	4	7	11	10	9	13	2
CRE	0	0	1	1	1	4	3	0

Figure 3 Trend in BIM-AI advantages

distinct evolutionary patterns aligned with technological advancements, construction industry needs, and research priorities, as derived from the temporal trend matrix.

The ASB category shows a steady increase, starting at two codes in 2018, rising to five codes in 2020, and peaking at 15 codes in 2024, before stabilising at six codes in 2025. AI–BIM integration plays a central role in automation and generative design (e.g. automatic modelling capabilities, structural optimisation, and generative design algorithms), as evidenced by the strong synergy with DPG and the peak of 15 codes in 2024. This integration of AI with BIM dimensions enables not only process automation but also the creation of innovative design solutions that were previously unattainable through traditional BIM alone. The stability and resurgence, particularly from 2023 to 2025, can be attributed to the sustained development of automated tools such as parametric modelling, automated façade analysis, and AI-driven simulations, as highlighted in studies like Darko *et al* (2020) and Andritsou *et al* (2024). The slight decline from 15 codes in 2024 to six in 2025 may indicate a maturation phase, focusing on refining existing tools rather than expanding their scope, as seen in Yevu *et al* (2025). The DPG category exhibits significant growth, starting at one code in 2018 and 2020, increasing to 10 codes in 2023, and peaking at 15 codes in 2024, with a slight decline to eight codes in 2025. This trend signals a paradigm shift toward leveraging AI to enhance design quality, productivity, and operational efficiency, aligning with the rise of generative design tools and BIM-based optimisation, as evident in studies by Balogun *et al* (2024) and Yevu *et al* (2025). The synergy between BIM and advanced AI algorithms has driven this increase, yielding more creative and efficient outcomes, particularly in areas like façade design and 3D BIM model creation.

KAI demonstrates the most dramatic growth, beginning at two codes in 2018, rising to five codes in 2020, and reaching a peak of 18 codes in 2024, before declining to six codes in 2025. This category's dominance, especially in 2024, reflects the industry's focus on leveraging AI-BIM for innovation, knowledge discovery, and cross-domain synergy, as noted in Saleh *et al* (2024) and Ploszaj-Mazurek and Rynska (2024). The peak in 2024, supported by contributions like global research momentum and digital transformation, underscores a research-driven surge, with the 2025 decline possibly indicating a shift toward practical implementation over innovation. The SSI category, absent in 2018 to 2020 (zero codes), shows a gradual rise, reaching five codes in 2022, 10 codes in 2023, and peaking at 11 codes in 2024, before declining to six codes in 2025. This delayed but steady growth reflects the construction industry's response to global pressures for sustainability and safety, driven by environmental regulations and safety standards, as noted in Mai *et al* (2024) and He *et al* (2025). The focus on real-time emissions estimation and advanced safety monitoring in 2024 and 2025 highlights AI-BIM's increasing recognition as a tool to address these challenges.

CAE grows from one code in 2018 to seven codes in 2020, peaks at 13 codes in 2024, and drops to two codes in 2025. This trend, with strong contributions in real-time multidisciplinary collaboration and inclusivity, as seen in Alavi *et al* (2024), reflects early adoption of collaborative tools in 2021 (11 codes) and 2022 (10 codes). The decline in 2025 may suggest a shift in focus toward productivity and sustainability, though the 2024 peak indicates a high point in accessibility enhancements. DMI increases from two codes in 2018 to six codes in 2020, peaks at 13 codes in 2024, and stabilises at five codes in 2025. This consistent performance, driven by real-time decision support and predictive capabilities, as noted in Andritsou *et al* (2024), underscores AI-BIM's role in improving decision-making processes, with the 2024 peak reflecting advanced trend identification and historical insights.

CRE remains the least prominent category, registering only four codes in 2023 and none in 2025. This limited representation should be interpreted in the context of return on investment (ROI) and technology adoption maturity in the AEC sector. Construction projects typically span 3 to 10 years, and the full cost-saving benefits of AI–BIM integration (e.g. reduced rework, optimised procurement, and predictive maintenance) often materialise only after the initial high investment in software, training, and system integration has been amortised. Industry studies indicate that digital technologies in construction commonly require 4 to 7 years to reach break-even and deliver measurable ROI (Blanco *et al* 2023, Oren 2023). Consequently, the low code count may reflect that the industry is still in the early- to mid-adoption phase and has yet to fully reap or systematically document these longer-term economic gains, rather than an absence of actual benefit. This gap highlights an important avenue for future longitudinal and empirical research. Future studies that track real-project ROI over full project life cycles would therefore be particularly valuable in quantifying CRE advantages that academic literature has not yet captured.

In summary, the temporal trend chart highlights the dynamic evolution of

Table 5 Co-occurrence matrix and co-occurrence of BIM-AI advantages categories

	ASB	DMI	DPG	KAI	SSI	CAE	CRE
Automation and scalability (ASB)	–	47	52	57	36	47	10
Decision making and insights (DMI)	47	–	42	47	34	43	10
Design and productivity (DPG)	52	42	–	54	36	44	10
Knowledge and innovation (KAI)	57	47	54	–	36	49	10
Sustainability and safety (SSI)	36	34	36	36	–	31	9
Collaboration and access (CAE)	47	43	44	49	31	–	10
Cost and resource efficiency (CRE)	10	10	10	10	9	10	–

AI-BIM integration, with ASB, DPG, and KAI leading in 2024 (15, 15, and 18 codes, respectively), driven by automation, design optimisation, and innovation. The rise of SSI (11 codes in 2024) reflects growing attention to sustainability and safety, while CAE (13 codes in 2024) and DMI (13 codes in 2024) underscore collaboration and decision-making advancements. The minimal focus on CRE suggests a need for targeted development.

The co-occurrence matrix is presented in Table 5, with its corresponding heatmap also illustrated based on this matrix. The matrix quantifies the frequency with which two advantage categories appear simultaneously across the dataset, derived from the temporal trends of AI-BIM integration from 2018 to 2025, as reflected in Figure 3. For example, ASB and DPG co-occurred 52 times, while CAE and CRE exhibited the lowest co-occurrence at 10 times.

The co-occurrence heatmap reflects the frequency with which two advantage categories – ASB, DMI, DPG, KAI, SSI, CAE, and CRE – appear together, indicating their interconnections and synergies. For instance, ASB shows the highest co-occurrence with KAI (57 times) and DPG (52 times). This strong linkage, particularly the 52 co-occurrences with DPG, reflects a deep synergy between automation and design enhancement, a pattern confirmed in recent studies, such as Balogun *et al* (2024), which focus on AI-driven optimisation in BIM workflows. Similarly, SSI demonstrates moderate co-occurrence with DPG (36 times) and ASB (36 times), suggesting that sustainability and safety are often addressed alongside enhanced design and automated processes, aligning with industry shifts noted in Mai *et al* (2024).

Conversely, CRE exhibits the lowest co-occurrence with other categories, with a maximum of 10 times with ASB, DMI, DPG, KAI, and CAE, and only nine times with SSI. This low co-occurrence, particularly the 10-time maximum, indicates that cost savings are less frequently viewed as a standalone advantage and more as an outcome of other categories, with long-term realisation anticipated as AI-BIM tools mature.

To summarise, the temporal trend analysis, as highlighted in Figure 3, reveals that DPG emerged as the dominant advantage from 2023 onward, surging from 13 codes in 2023 to 15 codes in 2024, and stabilising at eight codes in 2025, likely driven by the integration of generative design algorithms with BIM, as evident in works by Yevu *et al* (2025). In contrast, CAE experienced a sharp decline after peaking at 13 codes in 2024, dropping to two codes in 2025, possibly due to reduced demand for remote collaboration following the peak of hybrid work trends. Meanwhile, the co-occurrence heatmap of Table 5 demonstrates that ASB and KAI share the strongest linkage with 57 co-occurrences, reinforcing the critical role of automation in driving innovative practices within the BIM-AI ecosystem. These findings emphasise the growing importance of design, automation, and innovation, while highlighting gaps in cost efficiency, necessitating further research attention to enhance CRE integration.

DISCUSSION

This study addresses the fundamental question of the main benefits of integrating AI and BIM in the construction industry and how this integration can be leveraged for innovation and sustainability in AEC projects. The comprehensive systematic literature review, enriched by an expanded dataset of references from 2018 to 2025, reveals that AI-BIM integration not only tackles complex industry challenges but also unlocks transformative opportunities in efficiency, innovation, and sustainability. These findings extend beyond previous research, which often focused on technical or case-specific aspects (e.g. Pan & Zhang 2023, Zhang *et al* 2022), by providing a quantitative framework that elucidates the relationships and synergies among these benefits.

The meta-synthesis approach adopted in this study offers several notable strengths. By systematically translating and integrating findings from 65 diverse studies, it has enabled the construction of a higher-order conceptual framework and the identification of relational synergies (e.g. 57 co-occurrences between ASB and KAI) that would remain invisible in isolated reviews or single empirical studies (Zimmer 2006, Lachal *et al* 2017). This interpretive synthesis therefore provides a holistic, systemic perspective that directly addresses the fragmentation highlighted in the literature. Nevertheless, certain limitations must be acknowledged. As an inherently interpretive method, meta-synthesis relies on the researchers' judgment during coding, category development, and translation of concepts. Despite the use of two independent coders and documented inter-coder reliability checks, some degree of subjectivity in interpretation remains unavoidable. In addition, the analysis is constrained by the published literature, introducing the risk of publication bias toward positive outcomes and the exclusion of unpublished or non-English studies. Finally, the temporal trends for 2025 are based on incomplete data, which may moderate the observed decline in certain categories. These limitations are mitigated where possible through rigorous screening, quality appraisal via the CASP checklist, and explicit methodological transparency. Yet they underscore the need for future empirical validation of the proposed framework. The broad AI search term ensured inclusion of studies utilising ML, generative AI, and large language models, yet the inherent limitations of keyword-based retrieval remain.

The temporal trend analysis, as depicted in Figure 3, highlights a significant surge in DPG from 13 codes in 2023 to 15 codes in 2024, with a drop to eight codes in 2025, which can be attributed to the ongoing nature of the year and the incomplete inclusion of 2025 studies within the review period. This growth, surpassing earlier estimates, underscores a paradigm shift toward generative design algorithms and automation within BIM, corroborated by recent studies such as Balogun *et al* (2024) and Yevu *et al* (2025). The co-occurrence

matrix in Table 5 further reveals a robust synergy between ASB and DPG with 52 co-occurrences, and an even stronger linkage with KAI at 57 co-occurrences. This indicates that automation serves as a catalyst for design optimisation and innovative practices, a finding supported by Sacks *et al* (2022) and Mai *et al* (2024) on AI-driven optimisation.

CAE peaked at 13 codes in 2024, with a decline to two codes in 2025, which should be interpreted cautiously due to the incomplete data for the current year rather than a definitive shift away from remote collaboration. Though studies suggest that post-pandemic collaboration needs have stabilised, potentially reducing the urgency for digital accessibility tools, further data is need to confirm this trend. Similarly, CRE remains the least prominent, with a maximum of 10 co-occurrences with other categories and a peak of four codes in 2023, indicating that cost savings are often a secondary outcome rather than a primary focus, as reinforced by industry feedback on long-term economic benefits.

The strong interconnections – e.g. 57 co-occurrences between ASB and KAI, and 54 between DPG and KAI – highlight a research-driven ecosystem where innovation and productivity are deeply intertwined. SSI, with 36 co-occurrences each with ASB and DPG, reflects growing attention to environmental and safety standards, aligning with global regulations as noted in He *et al* (2025). These findings fill a critical gap in the literature by offering a holistic view of AI-BIM benefits, moving beyond isolated technical analyses to a relational framework.

Practically, these insights suggest that AEC stakeholders should prioritise investments in automation and design tools to enhance sustainability and efficiency. For instance, policymakers and project managers can develop integrated BIM-AI systems, leveraging the ASB-DPG synergy (52 co-occurrences) to optimise resource use and reduce environmental impact, as demonstrated in Andritsou *et al* (2024). The low CRE integration (maximum 10 co-occurrences) signals an opportunity for targeted research to address cost-related challenges, potentially through longitudinal studies on economic outcomes.

CONCLUSION

This study concludes by affirming the transformative potential of AI-BIM integration in the AEC industry, offering a comprehensive view of its benefits for innovation and sustainability as observed in current trends. The analysis reveals a significant rise in design and productivity enhancements, a strong synergy between automation and innovation, and a growing focus on sustainability, while cost efficiency remains underexplored, reflecting evolving industry priorities. This shift, driven by advancements in design tools supported by automation, suggests a promising direction for the field, with the limited focus on cost efficiency highlighting an area for future growth the relational patterns and temporal surges presented in the results (see Tables 4 and 5 and Figure 3). The incomplete data for 2025, due to the ongoing nature of the year and its partial inclusion in the review, advises caution in interpreting recent trends, yet the robust interconnections – such as the 52 co-occurrences between automation and design – provide a solid basis for progress. These findings, as evidenced by the co-occurrence matrix in Table 5 (e.g. 57 co-occurrences between ASB and KAI, and 52 co-occurrences between ASB and DPG) and the temporal trends shown in Figure 3 (with DPG and ASB both peaking at 15 codes in 2024), emphasise the growing importance of design, automation, and innovation, while highlighting gaps in cost efficiency. Future research should explore sub-code interactions and practical challenges like stakeholder adoption to enhance this understanding, while also investigating implementation hurdles and supply chain effects to offer deeper insights. The findings are summarised as:

1. The literature highlights the potential of AI–BIM integration to improve design processes, automation, and sustainability in AEC projects.
2. DPG surged in 2024/25, peaking at 15 codes in 2024 and reflecting a shift to generative design.
3. Strong synergy between automation and design (52 co-occurrences) drives innovation.
4. Within the analysed dataset, collaboration appeared in two codes in 2025, while cost efficiency reached its highest frequency (four codes) in 2023. These observations reflect patterns within the reviewed sample rather than definitive year-to-year trends.
5. A conceptual framework offers actionable insights for efficiency and sustainability.

It is suggested that future research focuses on co-occurrence analysis at the level of individual codes (such as "real-time decision support" and "enhanced automation") to identify more precise interactions between the benefits. Furthermore, investigating the implementation challenges and long-term effects of AI-BIM integration in the supply chain and collaboration between stakeholders could lead to a more comprehensive understanding. These findings provide practical guidance for AEC professionals and researchers to leverage the potential of these technologies to advance the industry.

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