AI-Assisted Data Modelling & Design: A Systematic Literature Review

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ABSTRACT

Purpose: This paper explores how artificial intelligence (AI) supports Data Modelling and Design (DM&D) across its lifecycle and how human-in-the-loop (HITL) mechanisms can enhance model quality in enterprise governance.

Methodology/Approach: A PRISMA 2020–guided systematic review (2023–2025) of Scopus, Web of Science, and ACM Digital Library identified 28 eligible studies. Evidence was synthesised along the DAMA P–D–C–O cycle, with a focus on HITL.

Findings: AI supports planning, building, reviewing, and managing data models through schema generation, enrichment, validation, and optimisation. Results vary with model accuracy, data quality, and semantic gaps. Effective use relies on HITL workflows such as propose–validate, tutoring, co-editing, and feedback loops. A scorecard combining technical, performance, efficiency, and governance indicators traceable via metadata helps demonstrate impact.

Research Limitation/Implication: Findings reflect studies published between 2023 and 2025; results may evolve as AI capabilities progress.

Originality/Value of paper: This study presents the first lifecycle synthesis of AI-assisted DM&D. It organises evidence from 28 studies, defines key HITL patterns for quality assurance, and outlines ways to evaluate AI's role in modelling governance. The findings provide a basis for further research and for developing frameworks that connect AI-driven modelling with enterprise data governance.

Category: Literature review

Keywords: data modelling and design; human-in-the-loop; data governance; artificial intelligence; systematic review

Research Areas: Management of Technology and Innovation; Quality by Design

1 INTRODUCTION

Data Modelling and Design is a cornerstone of modern data governance, translating business concepts into formalised data structures across conceptual, logical, and physical levels (Earley, Henderson, and Data Management Association, 2017). A well-designed data model forms the basis for FAIR (Findable, Accessible, Interoperable, Reusable) data — and thus underpins the quality of downstream data assets and analytical outputs (Pernici et al., 2025).

Despite this central role, persistent challenges remain. Studies show recurring difficulties with relationships, cardinalities, and labelling, underscoring the cognitive complexity of modelling (Rosenthal, Strecker and Snoeck, 2023). Learning to model data effectively, therefore, represents a demanding skill that requires both analytical and conceptual reasoning. Educational research shows that targeted feedback and visualisation can support this learning process by enhancing comprehension and collaboration among modellers (Köhnen et al., 2025).

While modelling remains cognitively demanding, artificial intelligence is emerging as a possibility to ease this complexity. Recent work shows that AI already supports several areas of data management, yet AI-assisted Data Modelling and Design is still limited (Stanek, 2025). By AI-assisted DM&D, we mean the use of AI to generate, validate, and translate modelling artefacts under auditable human-in-the-loop control, embedding quality-by-design across conceptual, logical, and physical layers.

Framed within the Quality 5.0 perspective, advanced technologies augment—rather than replace—human capabilities, balancing technological progress with ethical responsibility and sustainability (Maljugić et al., 2024; Depoo et al., 2025).

In this view, artificial intelligence is emerging as a viable means to ease modelling complexity while keeping decision authority and accountability with humans. Operationally, this implies auditable, human-in-the-loop governance that demonstrably improves model and process quality across Planning – Development – Control – Operations (P–D–C–O).

We see strong potential to enhance the quality and reusability of data models by strengthening human modelling capabilities through AI. In line with the Quality by Design principle, quality should be embedded into modelling processes from the outset and maintained throughout the entire lifecycle of data models, enabling sustainable improvements in data quality (Jiang et al., 2007). At the same time, it is essential to recognise that AI-generated outputs may still vary in reliability and therefore require critical human validation.

Guided by this motivation, we ask two research questions that together aim to reposition DM&D at the centre of AI-enabled governance:

RQ1: How does AI directly support Data Modelling & Design activities across the P–D–C–O cycle?

RQ2: How should human-in-the-loop arrangements be designed and measured to demonstrate improvements in model quality within enterprise governance workflows?

By addressing these questions, this study seeks to provide a comprehensive understanding of how AI influences data modelling and modellers themselves—its potential benefits, limitations, and associated risks. The insights gained are intended to inform future research and practical applications on how AI can improve data quality through more effective governance and management frameworks.

2 METHODOLOGY

2.1 Review design

We conducted a PRISMA 2020–guided systematic literature review to answer the research questions on AI-assisted data modelling and design in enterprise contexts, with particular attention to human-in-the-loop practices. The review was bounded by a January 2023–present window to reflect the surge of work on generative AI and large language models in data management, and it covered three major databases—Scopus, Web of Science (WoS), and the ACM Digital Library (ACM DL)—to ensure comprehensive coverage. The protocol—comprising search strategy, screening, full-text assessment, data extraction, and synthesis—followed the project outline and is summarised below.

2.2 Information sources and search strategy

Searches were conducted across Scopus, Web of Science Core Collection, and the ACM Digital Library from January 2023 onwards, restricted to English, peer-reviewed journal articles and conference papers within specified subject domains. We applied a pre-specified three-concept search protocol (data modelling × AI for modelling × human-in-the-loop) across Scopus, Web of Science Core Collection, and ACM Digital Library in Title/Abstract/Keywords fields, with limits to peer-reviewed English publications (2023–2025); database operators were adapted per platform. For a detailed breakdown of information sources, please refer to Table 1.

Table 1 – Information sources and search scope

Database	Time window	Document types	Subject filters	Notes
Scopus	Jan 2023–Sep 2025	articles; conference papers	Computer Science, Engineering, Decision Sciences	Three-concept protocol (DM × AI × HITL); fields: Title/Abstract/Keywords; limits: English; Articles/Conference Papers; 2023–2025; operator translation to Scopus syntax.
Web of Science Core Collection	Jan 2023–Sep 2025	articles; proceedings	Computer Science; Engineering; Management/Decision	Three-concept protocol (DM × AI × HITL); topic search; limits: English; Articles/Proceedings Papers; 2023–2025; operator translation to WoS syntax.
ACM Digital Library	Jan 2023–Sep 2025	journals; proceedings	Computer Science	Three-concept protocol (DM × AI × HITL); fields: Title/Abstract/ACM Subject; limits: English; 2023–2025; operator translation to ACM DL syntax.

2.3 Screening procedure

Eligibility criteria

Studies were included based on a clear link to DAMA-style Data Modelling & Design (conceptual, logical, or physical modelling) and the direct application of AI/ML to DM&D tasks. Exclusion criteria focused on work without an explicit data/schema-modelling link, as well as non-peer-reviewed or non-English sources. Detailed eligibility criteria are outlined in Table 2.

Table 2 – Eligibility criteria

Criterion type	Definition
Inclusion	DAMA-style data modelling & design (conceptual/logical/physical; schema design; ER/UML); AI assisting modelling tasks (schema matching/mapping, naming, constraint mining, documentation, impact); English; peer-reviewed; 'Enterprise Fit' (deployable in organisational contexts).
Exclusion	Statistical/simulation/predictive modelling without explicit data/schema modelling link; poster abstracts; non-peer-reviewed; non-English.

Deduplication

Duplicates (n = 119) and five incomplete records were removed using Rayyan's automated resolver (Ouzzani et al., 2016), followed by manual verification.

Title, abstract, and keyword screening

The remaining 538 records were independently assessed by two reviewers against predefined inclusion/exclusion criteria (pre-Enterprise Fit). Inter-rater agreement on this set was substantial (Cohen's $\kappa = 0.671$). Only records achieving both inclusion and Enterprise Fit consensus (n = 53) were advanced to full-text assessment. For detailed agreement metrics from the pre-Enterprise Fit stage, see Table 3.

Table 3 – Title/abstract screening: inter-rater agreement (κ), N=538 (pre-Enterprise Fit stage)

	Reviewer B: include	Reviewer B: exclude	Row total
Reviewer A: include	58	26	84
Reviewer A: exclude	19	435	454
Column total	77	461	538
Metric		Value	
Observed agreement (Po)		0.916	
Chance agreement (Pe)		0.745	
Cohen's κ		0.671	
Interpretation		Substantial (0.61–0.80)	

PRISMA flow

The comprehensive process of study selection, from initial identification of 662 records to the final inclusion of 28 studies, is visually represented in the PRISMA 2020 flow diagram (see Figure 1).

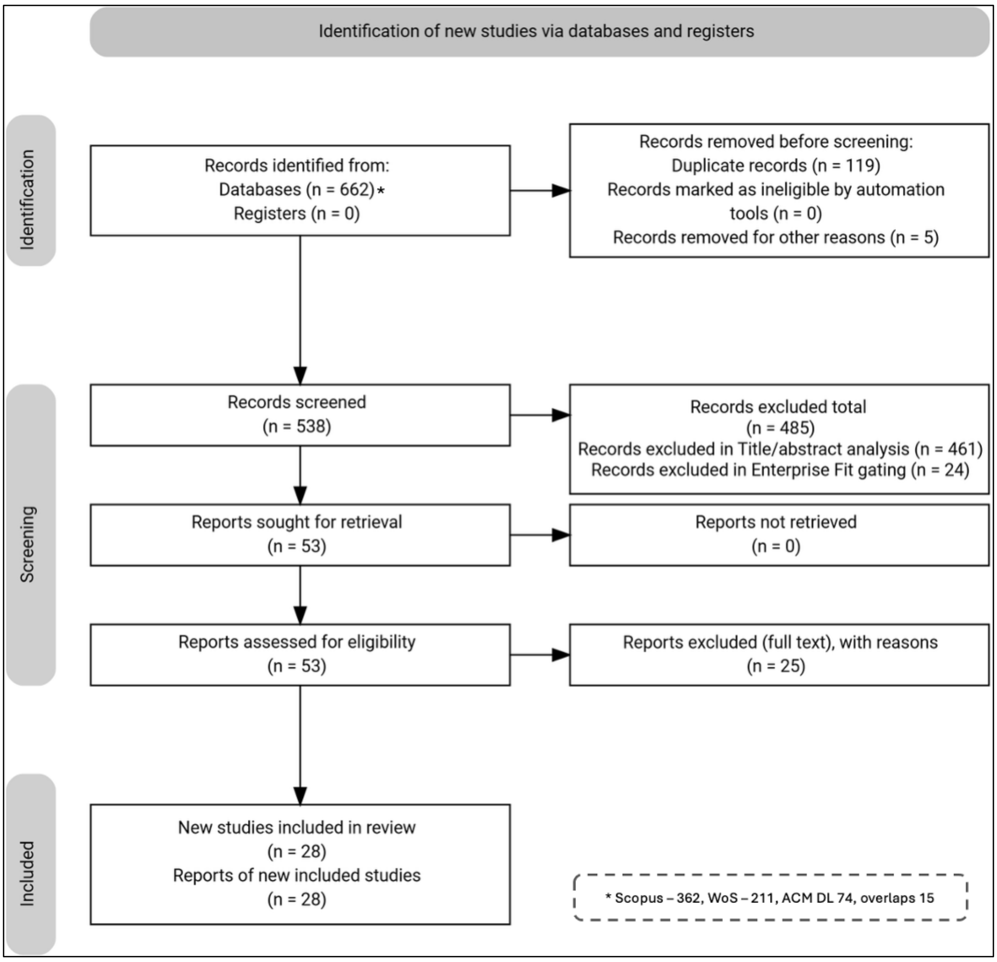

Figure 1 – PRISMA 2020 flow diagram (identification to inclusion). Diagram generated using the PRISMA2020 tool (Haddaway et al., 2022).

2.4 Quality assessment of primary studies

To ensure the reliability and validity of our findings, we conducted a systematic quality assessment of the 28 primary studies, based on Kitchenham's (2015) guidelines and criteria adapted from Mozaffari et al. (2024). This assessment evaluated the availability of the publication, the detailed description of methods, and the comprehensive presentation of results and evaluation metrics, and it was used descriptively, not as an exclusion criterion.

2.5 Data extraction and coding

Data extraction was conducted using a structured Excel template, double-coded with consensus, and the findings were synthesised along the DAMA P–D–C–O cycle. This framework covers the scoping of business concepts, the construction of conceptual, logical, and physical models, and their subsequent review, validation, and operational management (Earley, Henderson, and Data Management Association, 2017). For each study, we captured bibliographic metadata and key characteristics, including modelling phase, AI approach, HITL role, and data-quality dimensions. The detailed extraction codebook and variable dictionary are summarised in Table 4.

Table 4 – Extraction codebook (concise overview)

Category	Operationalisation	Example values
P–D–C–O phase	Stage of modelling cycle	Planning; Controll; Development; Operations
Modelling task	Where AI assists	discovery; matching; naming; constraints; documentation; impact
AI approach	Technique/method	LLM/NLP; transformer; knowledge graph; embeddings; ER algorithms
Evidence type	Nature of evidence	benchmark; experiment; case study; expert evaluation
HITL role	How humans intervene	propose→validate; co-editing; linting with approval
Data quality dimension	Quality lens	semantic consistency; PK/FK coverage; documentation completeness
Enterprise Fit	Deployability in org.	Y/N (+ notes)

As our conceptual frame, we adopt DAMA-DMBOK, which situates DM&D

3 RESULTS & DISCUSSION

This section summarises the results in relation to the research questions, beginning with findings from the systematic review and structured by the DAMA P–D–C–O cycle. A total of 28 studies were analysed.

3.1 AI support of DM&D tasks

To address the first research question (RQ1), this section explores how AI directly supports Data Modelling and Design activities across the P–D–C–O cycle.

Plan for data models (P)

In planning, AI partners in requirement elicitation and skill building, with RAG-based LLM tutors offering continuous in-process feedback rather than post-hoc evaluation (Ardimento et al., 2024). Agentic LLM systems can build, query, and iteratively refine knowledge graphs using retrieval-augmented generation and Semantic Web design patterns (Purohit et al., 2024). LLMs generate natural-language descriptions of conceptual models, though their accuracy decreases for complex relations unless explicitly prompted (Avignone et al., 2025). Such descriptions are especially useful for updating or repairing poorly documented models.

Importantly, LLMs can assist in formulating competency questions to guide ontology and model design, but expert panels remain essential to assess relevance, confirming that AI is a support tool, not a replacement for human expertise (Rebboud et al., 2025).

Similar to training LLMs on legislative corpora for enrichment (Colombo, Bernasconi and Ceri, 2025), organisations could train models on DAMA principles or internal rules to embed domain-specific practices. This aligns with the broader notion of fine-tuning LLMs on domain-specific data to improve task performance (Ma et al., 2023; Li et al., 2024). Likewise, the SchemaPile approach shows how enterprise-specific data and metadata can form training corpora for tailored modelling assistants (Döhmen et al., 2024). Furthermore, AI can automate analysis and mapping of properties in early modelling stages, supporting modellers by reducing manual workload (San Emeterio de la Parte et al., 2025).

Across these uses, HITL supervision is consistently emphasized through tutoring, expert validation, and feedback, with studies highlighting personalized tutoring and teachers as final evaluators (Ardimento et al., 2024), agent-based LLMs guided by user queries (Purohit et al., 2024), expert panels for assessing competency questions (Rebboud et al., 2025), fine-tuning that requires human data preparation and validation (Colombo, Bernasconi and Ceri, 2025), and interactive workflows where users iteratively refine or reject schema suggestions (Döhmen et al., 2024). Together, these examples underline that HITL is essential for ensuring quality and trust in AI-supported planning.

Build data models (D)

In the building phase, AI supports conceptual, logical, and physical modelling.

At the conceptual level, LLM-assisted pipelines enrich attributes, classify entities, and cluster concepts into property graphs that can be queried and checked for inconsistencies (Colombo, Bernasconi and Ceri, 2025). Shirvani et al. (2023) build an explicit type system for Freebase entities and relations to detect and correct inconsistencies, while Hu et al. (2025) use knowledge graphs to construct and predict relations for design optimisation, and agentic KG-based systems combine construction and reasoning (Purohit et al., 2024).

LMs increasingly interpret natural-language prompts to generate conceptual models that capture entities, relations, and properties for data specifications and UI design (Avignone et al., 2025; Cao, Jiang and Xia, 2025). This highlights AI's role as a requirement elicitation partner, especially with unstructured natural language input (Yordanova, 2025). Similarly, models have been proposed for generating NoSQL data models directly from natural-language descriptions (Asaad, 2023). Taken together, these studies show that AI can extend conceptual modelling from enrichment to direct generation, but mixed results underscore the need for HITL oversight to ensure semantic quality and manage complex relations (De Bari et al., 2024; Avignone et al., 2025).

At the logical level, hybrid ontology–KG–LLM frameworks outperform LLM-only methods in schema translation, though human validation remains essential (Mohsenzadegan et al., 2024; Ortega-Guzmán et al., 2024). A semantic similarity method has been proposed to map EXPRESS constructs to OWL, showing how AI can automate generating and converting model fragments across formal languages (Liu, Jian and Eckert, 2023). SchemaPile provides a large corpus of relational schemas that enables training specialised models for tasks such as identifying keys and structural rules (Döhmen et al., 2024). In parallel, bridges between relational and graph databases enable natural-language queries across data models (Jia et al., 2024),

At the physical level, self-tuning ML systems adapt schemas, partitioning, and indexing dynamically, but remain experimental beyond SQL-based environments (Mozaffari et al., 2024). LLMs also act as generic data operators in ETL tasks, though reliability requires monitoring (Ma et al., 2023).

Beyond these layers, recent evaluations show that while LLMs can generate UML class diagrams, their semantic quality and handling of complex relations are limited, highlighting the need for stronger human oversight in advanced modelling tasks (De Bari et al., 2024).

Overall, model generation emerges as a key theme: LLMs show promise in creating conceptual models from natural-language prompts, NoSQL specifications, regulatory requirements, and by automating mappings between formal languages (Asaad, 2023; Liu, Jian and Eckert, 2023; Avignone et al., 2025; Cao, Jiang and Xia, 2025; Yordanova, 2025). Their outputs lack consistent robustness, reinforcing the need for HITL validation and hybrid methods to ensure semantic accuracy and domain relevance.

Review for Data Models (C)

The review phase emphasises continuous quality control and validation. RAG-based assistants provide live feedback during diagram creation, while self-supervised transformers trained on UML corpora detect model smells such as improper decomposition or overly complex classes, reducing downstream costs (Alazba, Aljamaan and Alshayeb, 2024). Entity alignment helps identify duplicates and inconsistencies across heterogeneous knowledge graphs, strengthening governance and integration (Liu and Dai, 2023).

LLMs can verbalise ER schemas into natural language to support non-expert reviews, though accuracy drops for complex relations (Avignone et al., 2025).

Across these methods, HITL involvement is explicit, and consistency is often improved by cross-LLM validation or self-consistency techniques such as multi-sample generation (Ma et al., 2023). In addition, an assistant for quality assessment integrated into the data model design process has been proposed, indicating a feedback mechanism that explicitly involves expert review (van Renen, Stoian and Kipf, 2024).

Manage the Data Models (O)

In the management phase, AI supports documentation, governance, interoperability, and optimisation, with LLM-based schema-to-text generation improving accessibility for diverse stakeholders (Avignone et al., 2025). Knowledge-graph pipelines monitor quality dimensions—accuracy, consistency, completeness, timeliness, trustworthiness, and interoperability—surfacing inconsistencies during operation (Colombo, Bernasconi and Ceri, 2025). Hybrid translation frameworks and bridges between relational and graph databases ensure interoperability across heterogeneous platforms (Jia et al., 2024; Mohsenzadegan et al., 2024).

At the physical level, self-tuning mechanisms continue to adapt schema structures to workload demands (Mozaffari et al., 2024). Moreover, agentic LLMs are able to curate and improve the very knowledge graphs that they use, creating a feedback loop between model maintenance and AI reasoning (Purohit et al., 2024).

Active learning frameworks combine machine models with human feedback for iterative KG refinement (Kim et al., 2025). Other approaches explicitly explore the idea of self-improvement, where models refine their own outputs over time (Mo et al., 2025).

3.2 Human-in-the-loop in AI-supported DM&D

This section addresses RQ2 by outlining how human-in-the-loop arrangements can be designed and evaluated to improve model quality in enterprise governance.

Human involvement is essential for quality and trust in AI-assisted modelling. In planning, experts provide guidance through tutoring, panels, and iterative acceptance or rejection of AI-generated updates (Ardimento et al., 2024; Rebboud et al., 2025). In building, oversight ensures semantic accuracy when LLMs generate models from natural-language prompts or convert between formal languages, as outputs often remain incomplete and inconsistent (De Bari et al., 2024; Avignone et al., 2025). The review phase explicitly integrates HITL via expert validation, cross-LLM checks, and quality-assessment assistants that embed domain expertise into evaluation loops (Ma et al., 2023; van Renen, Stoian and

Kipf, 2024). Finally, in management, user feedback is central to active-learning frameworks that iteratively refine knowledge graphs, complementing machine-based models with human judgment (Kim et al., 2025).

The design of effective HITL arrangements requires a hybrid and iterative framework (Mohsenzadegan et al., 2024). AI systems can generate preliminary schema drafts, entity relationships, or descriptive annotations, which are then validated, refined, or corrected by human contributors ranging from domain experts to less experienced users (Ma et al., 2023; Cao, Jiang and Xia, 2025). Feedback loops are critical for iterative improvements and for capturing expert reasoning that can later be used to train smaller, task-specific models (Liu and Dai, 2023; Li et al., 2024; Hu, Wang and Wu, 2025; Kim et al., 2025). Attention must focus on contextual grounding, interpretability, and transparent human control of AI-generated outputs (Purohit et al., 2024; Cao, Jiang and Xia, 2025).

The impact of HITL processes in data modelling can be measured quantitatively, using metrics that capture both model accuracy and the efficiency of human contributions. For example, F1-score reflects improvements in detecting errors or anomalies (Alazba, Aljamaan and Alshayeb, 2024; Avignone et al., 2025), while annotation efficiency indicates how effectively expert input translates into higher model quality (Kim et al., 2025).

A comprehensive scorecard should integrate modelling-specific quality dimensions such as accuracy, consistency, completeness, timeliness, trustworthiness, interoperability, robustness, and adaptability (Mohsenzadegan et al., 2024; Colombo, Bernasconi and Ceri, 2025). Expert validation and panels are key to assessing the relevance and quality of AI-generated outputs (Rebboud et al., 2025).

A practical scorecard should combine four categories of indicators:

(i) Technical quality (accuracy, consistency, completeness, robustness) (Alazba, Aljamaan and Alshayeb, 2024; Mohsenzadegan et al., 2024; Mozaffari et al., 2024; Colombo, Bernasconi and Ceri, 2025; Kim et al., 2025; San Emeterio de la Parte et al., 2025);

(ii) Performance metrics (F1, precision, recall) (Alazba, Aljamaan and Alshayeb, 2024; Li et al., 2024; Mohsenzadegan et al., 2024; Mozaffari et al., 2024; Kim et al., 2025);

(iii) Process efficiency (annotation effort, acceptance rate, time-to-model) (Liu and Dai, 2023; Alazba, Aljamaan and Alshayeb, 2024; Ardimento et al., 2024; Mohsenzadegan et al., 2024; Cao, Jiang and Xia, 2025; Hu, Wang and Wu, 2025; Kim et al., 2025);

(iv) Governance impact (compliance, rework reduction, explainability) (Ardimento et al., 2024; Li et al., 2024; Purohit et al., 2024; Hu, Wang and Wu, 2025; Kim et al., 2025).

These dimensions link technical quality with evolving demands of integration, regulation, and sustainable model evolution. Ultimately, HITL should demonstrate improvements not only in technical metrics but also in clarity, transparency, and domain alignment, making data modelling frameworks adaptive and evidencing the added value of human oversight.

3.3 Discussion

Data Modelling & Design has been a core discipline for decades, though it has recently received less attention amid the rise of cloud computing and generative AI. High-quality data models are not theoretical constructs but practical foundations for reliable analytics, governance, and trustworthy AI.

This review shows that recent advances in AI are reshaping how Data Modelling & Design can be practised. Rather than replacing the modeller, AI extends human capability through intelligent assistance, feedback, and adaptive reasoning. The study offers an integrated view of these developments and outlines several novel contributions to the field.

First, this study provides the first comprehensive, lifecycle-oriented synthesis of AI use in Data Modelling and Design. By mapping 28 studies across the DAMA P–D–C–O cycle, we show that AI now supports every phase of modelling—from planning and schema generation to validation, documentation, and operations. Earlier work often focused on single tasks such as schema matching or ontology learning; our synthesis highlights the broader, systemic role of AI across the modelling lifecycle.

Second, we identify and typify Human-in-the-Loop (HITL) patterns that support effective AI-assisted modelling. These include propose→ validate workflows, co-editing, quality-assessment assistants, and active-learning frameworks. This typology clarifies how human input enhances accuracy, explainability, and governance, providing a basis for traceable and auditable HITL systems in enterprise environments.

Third, we link technical and governance perspectives through a scorecard-based evaluation framework. It connects four dimensions—technical quality, performance, process efficiency, and governance impact—into a single structure. By combining quantitative metrics such as precision and recall with governance indicators like compliance and explainability, it creates a bridge between model quality and organisational accountability.

Together, these findings confirm that AI already influences all key phases of data modelling while the human-in-the-loop remains essential for quality assurance and governance. The results point toward a more integrated and evidence-based understanding of how AI contributes to both modelling efficiency and trustworthiness in enterprise contexts.

The review shows that many current approaches remain at an early or experimental stage, often developed on limited datasets or simplified structures. Future research should advance toward cloud-integrated, agentic modelling platforms that combine AI-driven schema reasoning with human governance and versioned metadata. Such environments could foster interoperability between human modellers, AI systems, and enterprise data infrastructures, forming "collaborative modelling ecosystems."

Overall, the findings position Data Modelling & Design as a renewed strategic capability in the AI era. Rather than being displaced by automation, modelling becomes the point where human reasoning and machine intelligence meet. Models developed under human-AI collaboration tend to be more interpretable to both humans and machines, strengthening data quality, explainability, and sustainable enterprise practices.

4 CONCLUSION

AI-assisted Data Modelling & Design is an emerging field that already demonstrates tangible value across the modelling lifecycle. AI methods contribute to planning, construction, validation, and maintenance of data models, improving efficiency and enabling new forms of interaction. Yet their reliability and semantic precision still vary, underscoring the continued need for human oversight.

Human-in-the-loop mechanisms remain the key to trustworthy results. When properly embedded, they ensure that AI-generated artefacts align with domain logic, governance standards, and organisational context. Systematic evaluation using measurable indicators of quality, performance, process efficiency and governance can make these effects transparent and traceable.

This review provides a foundation for developing unified frameworks where AI and human expertise jointly shape data models and their governance. Future work should test these approaches in enterprise environments, linking AI-driven modelling to real-world data quality, interoperability, and sustainable data management practices.

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