

Generative Artificial Intelligence in Business Process Modeling: A Systematic Literature Review of Applications, Opportunities, and Limitations

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Abstract. *Generative Artificial Intelligence (GenAI) and Large Language Models (LLMs) are increasingly applied to Business Process Modeling, particularly for Business Process Model and Notation (BPMN). This paper presents a systematic literature review of recent research on GenAI-assisted Business Process Modeling. The review identifies the main application areas, opportunities, limitations, and research gaps. The findings show a shift from automated BPMN generation towards validation, interpretation, and collaborative AI-assisted modeling. However, challenges remain regarding semantic correctness, advanced BPMN constructs, standardized evaluation, and empirical validation. The review provides a conceptual synthesis of current capabilities, challenges, and future research directions.*

Keywords. Generative Artificial Intelligence, Large Language Models, Business Process Modeling, Business Process Model and Notation (BPMN), Process Model Generation, Process Model Validation

1 Introduction

Artificial Intelligence (AI), particularly Generative Artificial Intelligence (GenAI) and Large Language Models (LLMs), have attracted considerable attention in Business Process Management (BPM) due to their ability to understand and generate natural language (Zhao et al., 2023), creating new opportunities to automate tasks traditionally performed by business analysts and process modeling experts. As Filep and Molnár (2025) observe in their structured review, the integration of AI into business process modeling now extends beyond LLMs to include machine learning, natural language processing, and robotic process automation, signaling a broader shift towards intelligent, adaptive process ecosystems. Since business process knowledge is frequently documented as textual process descriptions (Nour Eldin et al.,

2024), LLMs have emerged as promising tools for transforming such descriptions into formal BPMN models while also supporting model interpretation, validation, and refinement (Ružička & Štancel, 2026).

Business Process Modeling represents a fundamental activity within BPM, enabling organizations to document, analyze, optimize, and automate their business processes (van der Aalst, 2013). BPMN has become the de facto standard for process modeling. It provides a standardized notation that facilitates communication between business and technical stakeholders while supporting process analysis and automation (Object Management Group, 2014). As emphasized by Mendling et al. (2010) and van der Aalst (2013), process models constitute a central organizational asset that supports process improvement and digital transformation initiatives.

The application of LLMs to Business Process Modeling has evolved considerably during the last few years. Early studies primarily investigated the feasibility of automatically generating BPMN models from textual process descriptions (Ružička & Štancel, 2026; Zang et al., 2026). Subsequent research shifted towards decomposing the modeling task into multiple stages by introducing structured intermediate representations that improve model consistency and facilitate validation (Nour Eldin et al., 2024; Nour Eldin et al., 2025). Building upon these developments, Licardo et al. (2026) proposed an interactive BPMN Assistant that enables users to iteratively create and modify process models through natural language. Safan and Köpke (2025a, 2025b) extended LLM-based modeling towards BPMN collaboration diagrams and introduced additional validation mechanisms.

More recently, Kourani et al. (2025a) demonstrated that LLMs can also support process model comprehension by enabling users to query existing BPMN models using natural language. Kourani et al. (2025b) provided one of the first comprehensive benchmark-based evaluations of LLM capabilities for Business Process Modeling. Chen (2025) extended LLM-based BPMN generation to smart contracts,

translating Solidity code into BPMN models through instruction tuning. This extension shows that LLMs can process structured inputs beyond natural language descriptions. These studies reflect a gradual transition from simple text-to-BPMN generation towards comprehensive AI-assisted support throughout the Business Process Modeling lifecycle.

Despite the growing maturity of the field, several important challenges remain unresolved, particularly regarding semantic consistency, incomplete support for advanced BPMN constructs, and the absence of standardized validation procedures. Semantic consistency between textual descriptions and generated BPMN models remains difficult to achieve (Drakopoulos et al., 2026; Nour Eldin et al., 2025). Support for advanced BPMN constructs is often incomplete (Licardo et al., 2026; Safan & Köpke, 2025b). Standardized validation procedures are largely absent, and empirical evidence under realistic conditions is limited (Kourani et al., 2025b). Consequently, the current research landscape remains fragmented, making it difficult to identify prevailing research directions, methodological trends, and unresolved research challenges.

Motivated by the rapid growth of this research field, this paper presents a systematic literature review of recent studies investigating the application of GenAI to Business Process Modeling. By synthesizing the reviewed literature, the study aims to identify the principal application areas, analyze the reported opportunities and limitations, and highlight the research gaps that should guide future research. Accordingly, this review addresses the following research questions:

RQ1: What are the principal application areas and research trends in GenAI-assisted Business Process Modeling?

RQ2: What capabilities and limitations of GenAI-assisted Business Process Modeling are reported in the existing literature?

RQ3: What research challenges and future research directions emerge from the current body of literature?

The paper is organized as follows. After presenting the applied research methodology, the findings of the systematic literature review are reported and discussed, followed by concluding remarks and directions for future research.

2 Research Methodology

This paper presents a systematic literature review reported in accordance with the PRISMA 2020 guidelines (Page et al., 2021). The review focuses on scientific publications investigating the application of GenAI, particularly LLMs, in Business Process Modeling using BPMN. To identify relevant studies, a structured literature search was conducted on May 25, 2026, using the Scopus and Web of Science (WoS) databases. The search queries combined terms related

to GenAI, LLMs, Business Process Modeling and BPMN.

The search returned 159 publications indexed in Scopus and 68 publications indexed in WoS, giving a total of 227 records. After merging the search results, duplicate publications were removed using Digital Object Identifier (DOI), publication titles and bibliographic metadata, reducing the dataset to 157 unique studies.

The search strategy and database selection followed established recommendations for conducting systematic literature reviews in information systems research (vom Brocke et al., 2015).

During the first stage, an initial screening of titles and abstracts was supported by ChatGPT as an auxiliary tool. Each publication was evaluated against four predefined criteria: Generative AI/LLM, Business Process Modeling, BPMN, and Empirical Evaluation. For every criterion, a binary decision (Yes/No) was assigned. The obtained results served exclusively as a preliminary recommendation and were not used to determine the final selection of papers.

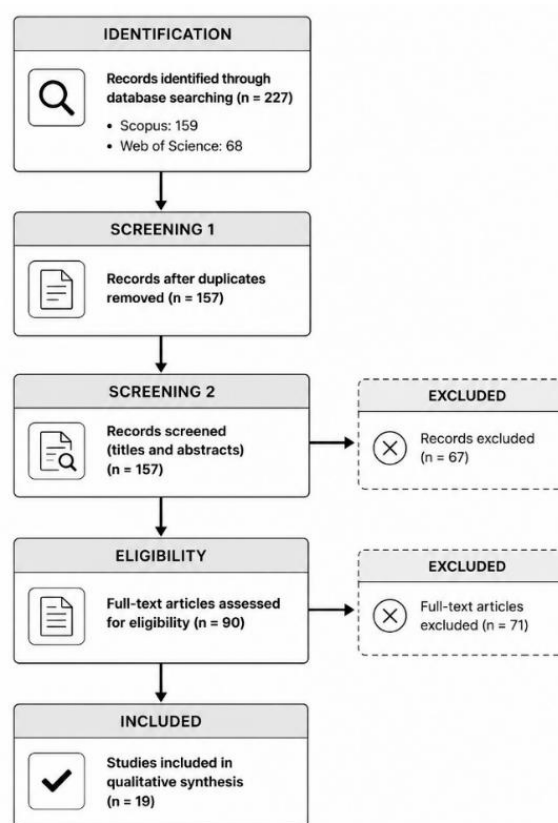


Figure 1. PRISMA flow diagram of the study selection process

The second stage relied entirely on manual assessment. All abstracts were reviewed and evaluated according to five predefined criteria: P1 – Generative AI/LLM, P2 – Business Process Modeling, P3 – BPMN, P4 – Empirical Evaluation, and P5 – Opportunities, Limitations or Challenges. Studies

satisfying P1 and P2 together with at least one of the remaining criteria were considered relevant for further analysis. This procedure resulted in a subset of 90 publications.

An additional qualitative assessment was performed to identify the core literature used in this review. Besides the predefined criteria, each publication was examined with respect to its relevance to the research objectives and its overall contribution to the application of GenAI in Business Process Modeling. Although the preliminary AI-assisted assessment was retained as a consistency check, the final decision was based exclusively on manual evaluation. As a result, 19 studies satisfying at least four of the five predefined criteria were selected for qualitative synthesis.

The complete study selection procedure is presented in the PRISMA flow diagram shown in Fig. 1. Following the concept-centric approach to literature reviews (Webster & Watson, 2002), the review synthesizes existing research by identifying the principal application areas, analyzing the reported opportunities and limitations, and highlighting research gaps that should guide future research.

3 Research Results

The results of the systematic literature review are presented in three parts. First, the geographical distribution of the 19 core papers is analyzed to identify the main research centres contributing to the field. Second, the temporal distribution of the 90 relevant papers is examined to reveal publication trends and the overall growth of research activity. Third, the core papers are classified according to their primary research purpose, providing a structured overview of the main application areas in GenAI-assisted Business Process Modeling.

Fig. 2 presents the geographical distribution of the 19 core papers based on the first author affiliation, grouped into four regional categories. European institutions dominate the sample, accounting for 78.9 % of all papers. The DACH region (Germany, Austria, and Switzerland) accounts for the largest share with 7 papers (36.8 %). The remaining European contributions are spread across seven countries, each represented by a single paper, together accounting for 42.1 %. Outside Europe, Asia contributes three papers (15.8 %), while Africa appears once (5.3 %). This distribution corroborates the leading role of Central European institutions in this domain, which is consistent with the region's established BPM research tradition and its strong presence in process modeling conferences and journals. Although contributions from other regions remain limited, the presence of papers

from Asia and Africa indicates a gradual internationalization of the field.

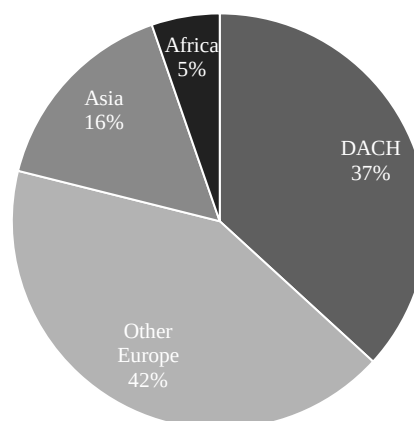


Figure 2. Geographical distribution of core papers by region¹

Fig. 3 shows the distribution of the 90 relevant papers by publication year. The number of papers rose steadily from 2 in 2022 to 12 in 2023, 25 in 2024, and peaked at 31 in 2025. The year 2026, with 20 papers already identified by May, suggests the upward trend is continuing.

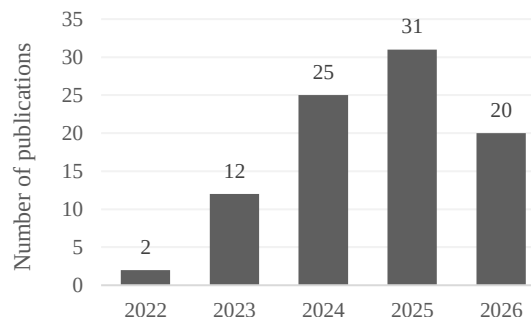


Figure 3. Distribution of relevant papers by publication year

The qualitative analysis of the selected studies identified four predominant research purposes: generation, validation, verification, and interpretation. Generation refers to the automated creation of BPMN models from natural language descriptions (e.g., Nour Eldin et al., 2025; Licardo et al., 2026). Validation encompasses the assessment of model quality, correctness, and semantic alignment (e.g., Drakopoulos et al., 2026; Safan & Köpke, 2025b). Verification involves formal property checking (e.g.,

¹ Based on 19 core papers included in the systematic literature review.

Safan & Köpke, 2025a; Kourani et al., 2024). Interpretation focuses on explaining and querying existing process models using LLMs (e.g., Kourani et al., 2025a). Table 1 maps the 19 core papers according to these categories.

Table 1. Classification of core papers by primary research purpose

Category	No. of papers	Perc.
Generation	12	63.2 %
Validation	4	21.1 %
Verification	2	10.5 %
Interpretation	1	5.3 %

Model generation clearly dominates the current research landscape, representing 12 of the 19 core studies (63.2 %). Validation is addressed in four studies (21.1 %), followed by verification (2 studies, 10.5 %) and interpretation (1 study, 5.3 %). Taken together, these results suggest that although automated BPMN generation remains the primary research focus, increasing attention is being devoted to complementary activities aimed at improving model quality, correctness, and usability.

4 Discussion

The reviewed literature demonstrates significant progress beyond initial experiments with automated BPMN generation. Despite differences in objectives, methodologies, and implementation approaches, several common trends emerge regarding the current capabilities of LLM-based solutions, their limitations, and the research challenges that remain to be addressed.

4.1 Current State of AI-Assisted Business Process Modeling

Current research on GenAI-assisted Business Process Modeling is strongly oriented towards BPMN model generation. However, the reviewed studies also indicate that the field is gradually expanding beyond simple text-to-model transformation towards more comprehensive AI-supported modeling workflows. This evolution is reflected in the variety of approaches proposed for generating, refining, and supporting BPMN models.

Most approaches to BPMN model generation assume that information required to construct a BPMN model can be extracted from natural language process descriptions and represented in a structured form suitable for automated modeling (Nour Eldin et al., 2025; Ružička & Štancel, 2026; Zang et al., 2026).

Several studies have demonstrated this concept through prototype systems such as Process Copilot (Caesar et al., 2025), BPMN Assistant (Licardo et al., 2026), Nala2BPMN (Nour Eldin et al., 2025), and BPMN-Chatbot++ (Safan & Köpke, 2025b). These solutions pursue the same objective: reducing the effort required to transform informal business knowledge into formal BPMN models.

An emerging trend in recent research is the growing adoption of multi-stage modeling workflows. Instead of generating BPMN models directly from textual descriptions, several authors introduce structured intermediate representations that separate text interpretation from model construction (Nour Eldin et al., 2024; Licardo et al., 2026; Safan & Köpke, 2025b). Boujmil and Chebil (2025) take a different hybrid approach, combining a traditional Natural Language Processing (NLP) pipeline with GPT-4 through prompt-guided fusion. Their method reduces overgeneration of activities and gateways and improves parallel gateway detection, showing that hybridization can work at the level of model synthesis, not just through intermediate representations. Researchers use intermediate representations, such as JavaScript Object Notation (JSON), formal specifications, and Partially Ordered Workflow Language (POWL) models, to enable partial verification before generating the final BPMN model. This decomposition not only improves model consistency but also enables domain experts to validate intermediate results before completing the modeling process.

The adoption of intermediate representations is motivated not only by technical implementation considerations but also by the need to improve transparency, verification, and user interaction throughout the modeling process. By separating semantic interpretation from BPMN model construction, these approaches reduce the complexity of the generation task and enable incremental verification of process information before the final model is produced. Such decomposition also facilitates user intervention, allowing domain experts to review and refine intermediate results without modifying the complete BPMN model. Consequently, intermediate representations contribute not only to improved model consistency but also to greater transparency and explainability throughout the modeling process (Nour Eldin et al., 2024; Licardo et al., 2026).

LLMs are increasingly viewed as collaborative assistants rather than autonomous model generators. Systems such as BPMN Assistant, BPMN-Chatbot++, and Nala2BPMN support iterative interaction in which users progressively refine process models through natural language instructions. Rather than relying on a single prompt, these approaches adopt iterative prompting strategies that combine user feedback with successive model refinements (Licardo et al., 2026; Safan & Köpke, 2025b). Taken together, these observations suggest that the quality of AI-assisted

Business Process Modeling depends not only on the capabilities of the underlying LLM but also on the design of prompts, the structure of user-system interaction, and the active involvement of domain experts throughout the modeling process. Business Process Modeling therefore evolves from a one-step generation task into a collaborative process in which human expertise and LLM capabilities complement each other.

The growing maturity of LLM-based modeling approaches has also broadened the scope of their application. Recent studies further extend the role of LLMs beyond BPMN model generation by enabling users to interact with existing process models through natural language. Instead of manually analyzing process diagrams, users may query process logic, request explanations of individual activities, or explore relationships between process elements using conversational interfaces. Alharbi et al. (2024) demonstrate this through AIPA, an LLM-based assistant that supports such interactions. Kourani et al. (2025a) extend this line of work with a more comprehensive framework and tool evaluation. Muttillio et al. (2025) explore a different direction, using LLMs to generate synthetic modeling traces and BPMN artifacts for training intelligent modeling assistants in data-scarce environments. While human-generated data remains superior, their results indicate that synthetic data can help address the cold-start problem in process modeling recommenders. These developments suggest that the role of LLMs is gradually extending beyond process generation towards broader support for process understanding and knowledge-intensive modeling activities. At the same time, they also expose several limitations that must be addressed before such approaches can be reliably adopted in practice.

4.2 Challenges and Future Research

Despite the considerable progress achieved in recent years, the reviewed studies consistently indicate that current LLM-based approaches still rely on human supervision or complementary validation mechanisms, suggesting that fully autonomous Business Process Modeling has not yet been achieved. Across the analyzed studies, semantic correctness emerges as the most persistent challenge. A syntactically valid BPMN model does not necessarily preserve the business logic expressed in the original textual description. Drakopoulos et al. (2026) show that this is particularly problematic when processes involve complex decision structures, exception handling, or parallel execution, while Nour Eldin et al. (2025) observe similar issues with incomplete or ambiguous process descriptions. This observation underscores that evaluating generated models solely against BPMN syntax is insufficient and that greater attention should be devoted to semantic fidelity between textual requirements and the resulting process model. A related concern is data privacy, as

most LLM-based modeling approaches rely on cloud-based services. Apaydin and Zisgen (2025) address this by proposing a pipeline that uses locally deployed, fine-tuned LLMs to generate process models, demonstrating that smaller open-source models can achieve competitive performance while preserving data confidentiality. Taken together, these findings suggest that future research should explore hybrid deployment strategies that balance model capability with privacy requirements.

Beyond semantic correctness, current limitations also concern both the scope of BPMN support and the evaluation of AI-assisted modeling approaches. While existing solutions successfully generate the core BPMN elements, advanced constructs such as collaboration diagrams, data objects, pools, and lanes remain only partially supported (Licardo et al., 2026; Nour Eldin et al., 2025). In addition, the reviewed studies employ different benchmark datasets, evaluation metrics, experimental settings, and LLM architectures, making a direct comparison of reported results difficult. Real organizational processes frequently depend on these constructs. For processes with complex data-activity relationships, Köpke, Bergenthum, and Kovář (2025) argue that even full BPMN support may be insufficient and propose object-centric modeling as an alternative. Extending LLM capabilities beyond basic process structures should therefore be a priority for future research.

While several studies propose quantitative evaluation procedures, a commonly accepted benchmarking framework has yet to emerge. Establishing standardized datasets and evaluation protocols would improve the reproducibility of future studies and facilitate objective comparison between different modeling approaches.

The reviewed studies consistently indicate that reliable AI-assisted Business Process Modeling cannot yet be achieved through a single prompt or a single LLM invocation. Instead, the most promising approaches combine structured intermediate representations, iterative prompting, and formal validation procedures, all combined with expert supervision. Alayón et al. (2026), for instance, demonstrate this through a two-stage multimodal pipeline where NotebookLM extracts process structure from video, while ChatGPT generates BPMN XML, with domain experts validating the final models. Similarly, Licardo et al. (2026) rely on iterative user feedback and JSON intermediate representations to refine BPMN models. Rather than replacing domain experts, these approaches position LLMs as decision-support tools operating within human-supervised modeling workflows.

The identified research challenges also outline several important directions for future work. In particular, future research should focus on improving semantic fidelity, extending support for advanced BPMN constructs, establishing standardized benchmarking procedures, and developing human-

centered AI-assisted modeling environments. Although empirical evaluation is reported in most reviewed studies, validation is predominantly conducted using prototype implementations, benchmark datasets, controlled experiments, or limited case studies. Evidence from long-term deployment, organizational adoption, and routine use of AI-assisted Business Process Modeling solutions in operational business environments remains largely absent. Consequently, future research should place greater emphasis on longitudinal evaluations and industrial case studies to better understand the practical impact and organizational adoption of these approaches.

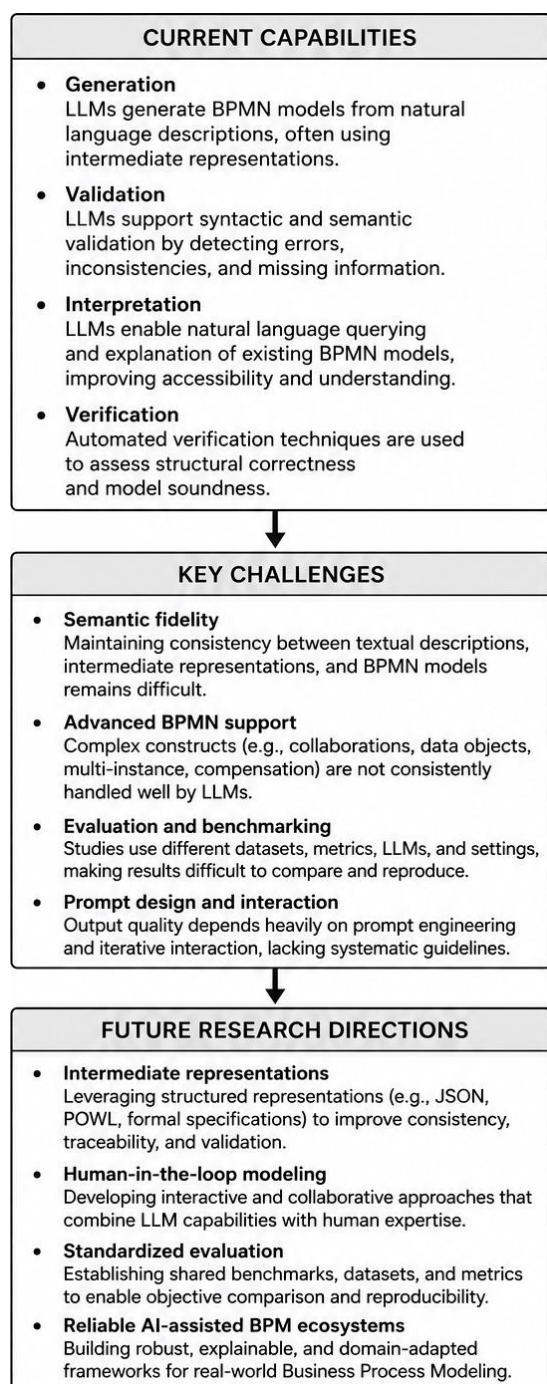


Figure 4. Summary of capabilities, challenges, and future directions

To consolidate these findings, the present review provides a conceptual synthesis of the current state of GenAI-assisted Business Process Modeling, structured around three complementary dimensions: capabilities, challenges, and future research directions. Rather than proposing a prescriptive framework, this synthesis represents an integrated interpretation of the reviewed studies, bringing together fragmented evidence into a coherent perspective. Fig. 4 summarizes this conceptual synthesis by illustrating how the current capabilities of GenAI-assisted Business Process Modeling reveal persistent challenges, which in turn define the principal priorities for future research.

5 Conclusion

This systematic literature review examined how GenAI is being applied to Business Process Modeling and synthesized current evidence on its capabilities, limitations, and future research directions.

The qualitative synthesis reveals that current research remains predominantly focused on automated BPMN model generation, while progressively expanding towards model validation, verification, interpretation, and interactive modeling support. This evolution reflects a broader shift from isolated text-to-model generation towards collaborative AI-assisted modeling approaches that integrate intermediate representations, iterative prompting, validation mechanisms, and human expertise. Overall, these findings demonstrate that the principal application areas of GenAI-assisted Business Process Modeling have expanded well beyond automated model generation, illustrating the rapid evolution and diversification of research in this field. The role of LLMs is therefore evolving from standalone model generators towards intelligent assistants supporting multiple phases of the Business Process Modeling lifecycle.

The reviewed studies demonstrate that recent advances in GenAI have substantially improved the capabilities of AI-assisted Business Process Modeling, particularly in automated model generation, process interpretation, interactive modeling support, and the integration of intermediate representations. Nevertheless, several important challenges remain unresolved. Current evidence consistently highlights issues related to semantic fidelity, limited support for advanced BPMN constructs, the absence of standardized evaluation frameworks, and the need for more comprehensive empirical validation. Addressing these challenges is essential for improving the reliability, transparency, and practical applicability of AI-assisted Business Process Modeling solutions.

The findings should be interpreted in light of several limitations. The review focuses specifically on BPMN and relies on a qualitative, concept-centric synthesis of 19 core papers selected from a broader set of 90 relevant publications. In addition, the literature search was limited to peer-reviewed publications indexed in Scopus and Web of Science at a specific point in time, potentially excluding recent preprints, emerging publication venues, and domain-specific contributions not indexed in these databases. Furthermore, the review did not employ backward or forward snowballing techniques. Future reviews could complement database searches with backward and forward snowballing to identify additional relevant studies. These limitations do not undermine the identified trends but indicate that the results should be interpreted as a structured snapshot of a rapidly evolving research field.

The main contribution of this review is a structured synthesis of current research that integrates the identified application areas, existing limitations, and emerging research directions into a coherent perspective on the evolution of GenAI-assisted Business Process Modeling. The findings suggest that future progress will depend not only on advances in LLM capabilities but also on the development of reliable validation mechanisms, standardized evaluation practices, broader organizational validation, and human-centered AI-assisted modeling frameworks capable of supporting complex real-world business processes.

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