Goal-Oriented Requirements Engineering: An Updated Systematic Mapping Study (2021–2025)

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Abstract. This paper presents a Systematic Mapping Study (SMS) on Goal-Oriented Requirements Engineering (GORE), covering research publications from 2021 to 2025. The study extends previous mapping efforts in the field, particularly the work of [7], which analyzed the period from 2016 to 2020, allowing a comparison of recent research trends. Based on an analysis of 71 primary studies, the mapping examines publication venues, research contribution types, and application domains related to GORE. The results indicate a relatively stable publication volume during the analyzed period, with a balanced distribution between conference proceedings and journal articles. At the same time, the findings suggest changes in contributions, with more studies proposing new approaches than incremental improvements to existing methods. Another observed trend is the growing integration between GORE and artificial intelligence techniques, particularly from 2022 onwards. Some studies explore the use of Large Language Models (LLMs) to support activities such as requirements elicitation, analysis, and goal model generation. The mapping provides an updated overview of the research landscape, indicating that GORE research is progressively incorporating automated and AI-supported techniques, reflecting broader developments in software engineering research and practice.

Keywords: Goal-oriented Modeling · Requirements Engineering · Systematic Mapping Study

1 Introduction

Goal-Oriented Requirements Engineering (GORE) is a well-established approach to support the early phases of requirements elicitation, analysis, and validation. Previous mapping studies indicate that the scientific community continues to actively expand models, notations, and techniques for analysis, adaptability, and process automation [7].

The development of complex and large-scale software systems requires a rigorous and methodical discipline to ensure that the final product satisfies stakeholders' needs. In this context, Requirements Engineering is widely recognized as the most critical phase of the software lifecycle, as failures in understanding, eliciting, or specifying requirements often lead to project delays, budget overruns, and low-quality products [7].

In this scenario, GORE has emerged as a highly successful paradigm. GORE models, such as i* (i-star), KAOS, and the NFR Framework, are based on the premise that both functional and non-functional requirements should be derived from and justified by high-level strategic goals [13]. GORE has proven to be particularly effective in domains that require high levels of criticality and adaptability, such as Self-Adaptive Systems [28], Systems of Systems (SoS) [1], and Safety-Critical Systems [32].

Despite the maturity of the field, the Software Engineering landscape has undergone a radical transformation in recent years. The emergence and widespread adoption of Artificial Intelligence (AI) and Large Language Models (LLMs) have introduced new challenges and opportunities for Software Engineering [10].

The objective of this study is to conduct a mapping and critical analysis of the scientific production in Goal-Oriented Requirements Engineering (GORE) from 2021 to 2025. This work seeks to identify not only research trends but also structural transformations in the GORE ecosystem, considering the evolution of approaches, the nature of contributions (new methods, models, tools, implementations, and empirical studies), as well as existing gaps in the field.

In addition to quantifying and classifying the published works, this study aims to understand how recent research has reshaped classical principles of goal-oriented modeling, particularly in light of the increasing incorporation of artificial intelligence, machine learning techniques, dynamic adaptation mechanisms, and hybrid analysis models. Thus, this mapping intends to provide an interpretative view of the current landscape, highlighting opportunities for innovation and unresolved challenges in the contemporary literature.

This paper presents a Systematic Mapping Study (SMS) guided by the PRISMA methodology [25], with three central research questions related to annual scientific production trends, types of contributions, and types of target systems. The study adopts a search strategy across the ACM, ScienceDirect, Scopus, and Web of Science databases.

After the search process, the methodology is described (selection criteria and extraction process), followed by the presentation of quantitative and qualitative results, along with a discussion of the obtained findings. The conclusion provides an overview of GORE between 2021 and 2025, highlighting its main approaches, applications, and observed trends.

This study provides the following contributions: (i) An updated systematic mapping of GORE literature (2021–2025); (ii) A comparative analysis with the previous period (2016–2020); (iii) The identification of emerging trends, including Generative GORE and Runtime GORE; (iv) A discussion of research gaps and future directions.

Methodology

This study followed the PRISMA methodology [25] in conducting the Systematic Mapping Study (SMS). The process was divided into three main stages: planning, mapping execution, and results analysis.

2.1 A. Definition of Research Questions (RQs)

The research questions were based on the work of Delima et al. [7] and were defined as follows:

- RQ1: What is the trend of GORE research over the last five years?
  Justification: RQ1 aims to determine the development trends of GORE research. The trend is analyzed based on the number of publications per year and the types of research contributions in GORE for each year.
- RQ2: What types of contributions have been made to GORE research?
  Justification: RQ2 aims to identify the types of contributions provided by the reviewed studies. These contributions offer insights into how GORE relates to other methods or approaches for automating and improving the quality of Requirements Engineering (RE). This information enables the identification of opportunities for future research in GORE.
- RQ3: What types of systems have been developed using GORE?
  Justification: RQ3 aims to identify the types of systems in which GORE has been applied within the Requirements Engineering process.

2.2 Search Strategy and Data Sources

To conduct this systematic mapping, the PRISMA methodology [25] was adopted, following the stages of planning, review execution, and results analysis. The searches were performed in the ACM Digital Library, ScienceDirect, Scopus, and Web of Science databases, using the search string "goal model" AND "requirement engineering". Although Delima et al. [7] did not formally report their search string, their search was based on the same keywords; the present study formalizes this strategy using explicit Boolean operators to improve reproducibility, while preserving comparability with the previous period. This string reflects a scope centered on goal modeling within RE rather than RE in general.

2.3 Screening and Study Selection Process

Inclusion and exclusion criteria were applied to ensure that only studies directly related to the research scope were considered.

After the initial identification, a screening process was conducted through the reading of titles, abstracts, and keywords, followed by a full-text review of potentially eligible articles. Finally, the data extracted from the selected studies were organized and analyzed to identify trends, contributions, and gaps in the recent literature.

– Inclusion criteria: (i) The study addresses GORE, goal modeling, or Requirements Engineering; (ii) The study was published between 2021 and 2025; (iii) The study is available in full text.
– Exclusion criteria: (i) The study is not peer-reviewed; (ii) The study is not written in English; (iii) The study is a final undergraduate project, thesis, or dissertation.

The article search, based on the aforementioned criteria, resulted in a total of 327 studies. From this total, 4 duplicate studies were removed. Of the remaining 323 studies, 249 were excluded based on abstract screening. The remaining 74 studies were selected for full-text reading. After reviewing all 74 studies, 3 were excluded for meeting the exclusion criteria. At the end of the selection process, 71 studies were included as they addressed the research questions proposed in this systematic mapping.

Figure 1 presents the flow diagram, based on the PRISMA methodology [25], illustrating the stages of the study selection process.

3 Classification Framework and Selected Studies

This study extends Delima et al. [7] — the most recent mapping covering the immediately preceding period (2016 -2020) and the only one adopting equivalent search criteria and contribution categories — enabling direct comparison between periods. Other reviews either cover earlier periods [13] or address more specific sub-topics. The classification framework below is adapted from [7].

– Tool: Software artifacts supporting modeling, analysis, or automation.
– New Approach: Novel models, frameworks, or techniques that extend the field.
– Method Development: Incremental improvements to existing GORE languages or techniques.
– Implementation: Practical application of GORE in systems or prototypes.
– Study and Method Evaluation: Empirical analysis of existing methods or tools.

Table 1 summarizes the number of studies per contribution category, providing a high-level overview of the distribution of research efforts.

Table 1. Distribution of studies by contribution category.

Category	Number of Studies
Tool	3
New Approach	41
Method Development	8
Implementation	9
Study and Method Evaluation	10
Total	71

Next, each category is discussed.

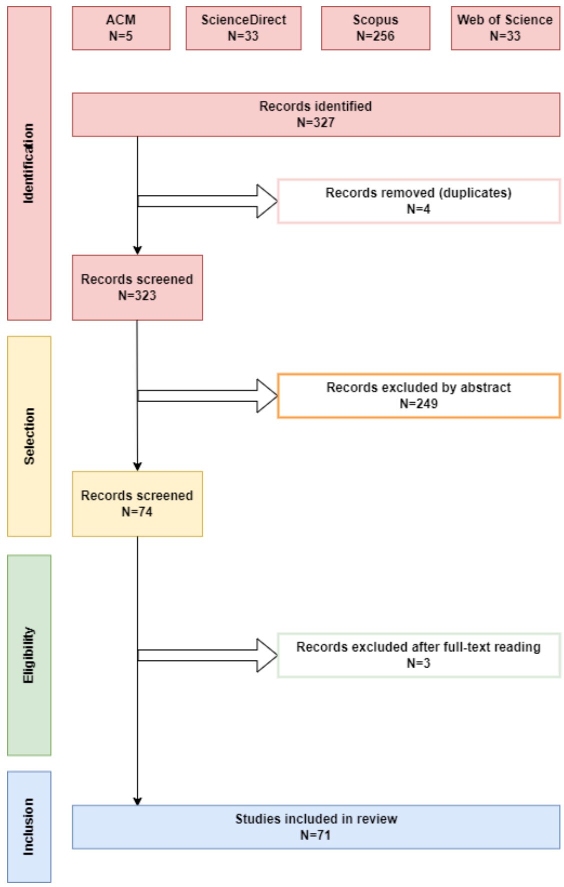

Fig. 1. Selection flow diagram.

3.1 Tool

The Tool category includes studies that implement software artifacts to support GORE activities such as validation, prioritization, and monitoring. These works reflect a shift toward automation and practical applicability.

Examples include tools for integrating GORE into *DevOps* environments [2], supporting the analysis of modeling processes [15], and prioritizing goals using *fuzzy logic* [4]. Overall, these tools demonstrate how GORE is increasingly supported by automated mechanisms and integrated into real-world development workflows.

3.2 New Approach

The New Approach category represents the dominant trend in recent GORE research, focusing on automation, accessibility, and integration with modern development practices.

Some works aim to bridge the gap between informal and formal representations, such as the automatic generation of goal models from *user stories* [12]. Others focus on improving model quality through automated detection of structural issues using rules and metrics [23, 22].

More comprehensive approaches propose end-to-end automation of the requirements engineering process, combining GORE with natural language processing techniques [6]. Additionally, lightweight frameworks integrate GORE into agile and security-oriented practices, enabling early consideration of quality attributes such as security and privacy [27].

Overall, these studies indicate a shift from traditional modeling toward automated, integrated, and practice-oriented approaches.

3.3 Method Development

Studies in this category focus on extending GORE through new formal mechanisms and analytical techniques.

Examples include methods that combine goal modeling with optimization to support decision-making [3], as well as extensions of iStar 2.0 to incorporate uncertainty through probabilistic effects and utility functions [20]. Other works address usability and practical adoption by proposing lightweight evaluation techniques based on goal dependencies [16].

These contributions reflect a continued effort to enhance the analytical capabilities of GORE while improving its applicability.

3.4 Implementation

The Implementation category highlights how GORE is applied in real-world systems and practical scenarios.

Some studies demonstrate the use of GORE for reengineering legacy systems, making implicit requirements explicit and guiding architectural improvements [29]. Others apply GORE from early development stages to connect stakeholder goals with system models in domains such as environmental monitoring [31].

More advanced implementations integrate GORE into runtime environments, enabling goals to influence system behavior through model-driven approaches [21]. Additionally, GORE has been used to support continuous evaluation of usability by transforming goals into observable metrics derived from user behavior [19].

These studies show that GORE is evolving from a design-time activity to an operational component in software systems.

3.5 Study and Method Evaluation

This category includes studies that evaluate the effectiveness, usability, and limitations of existing GORE approaches.

Some works highlight challenges in handling model evolution, particularly regarding traceability and consistency [17]. Others focus on usability, identifying barriers such as learning curve and artifact clarity [26].

There are also studies exploring new dimensions, such as emotional goals in requirements engineering [30], and the use of social goal models to identify security risks [8].

Overall, these evaluations reveal important gaps in current approaches, particularly related to usability, scalability, and adoption in practice.

4 Results and Discussion

The research questions were answered as follows:

RQ1: What is the trend of GORE research over the last five years?

Based on the 71 selected studies published between 2021 and 2025, the distribution of articles per year was: 2021 (12 studies), 2022 (15 studies), 2023 (17 studies), 2024 (15 studies), and 2025 (12 studies).

Regarding the proportion of publications in journals and conference proceedings, the results were 53.52% and 46.48%, respectively. Consistent with the findings of Delima et al. [7], the trend of GORE research can be considered stable over the analyzed period, as illustrated in Figure 2.

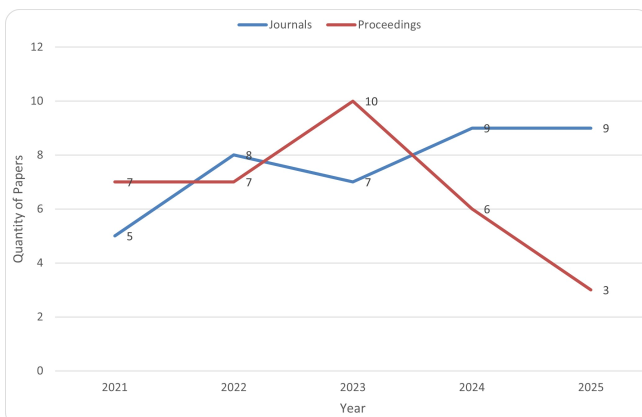

Fig. 2. Contribution of journal and conference papers per year.

RQ2: What types of contributions have been made to GORE research?

The contributions of each category by year of publication are presented in Figure 3.

The analysis of Figure 3 suggests a significant difference between the New Approach category and the other categories, indicating that new approaches represent the dominant contribution type in the analyzed period. Figure 4 presents the percentage distribution of each category.

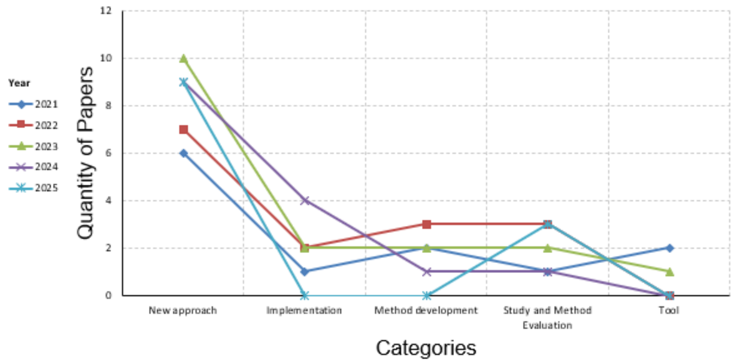

Fig. 3. Contribution of each category by publication year.

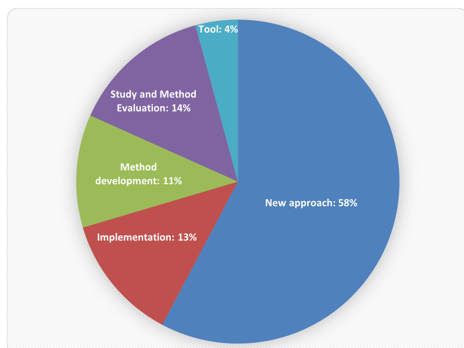

Fig. 4. Percentage distribution of each category.

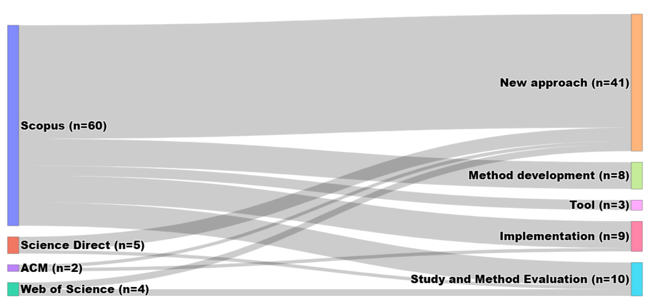

Fig. 5. Contribution of databases to each category.

In addition to the percentage distribution, a visualization of the contribution of each database to each category was generated (Figure 5).

RQ3: What types of systems have been developed using GORE?

GORE has been applied to a variety of real-world and experimental systems, particularly for runtime monitoring and adaptation. Examples include the instrumentation of goals in flight software for mini-satellites [18]. There are also applications in critical transportation systems [14], enabling the handling of vulnerabilities and variability in railway systems. In infrastructure and emergency services, GORE has been used for the discovery and assurance of non-functional requirements in seismic alert systems [29]. Additionally, there are applications focused on socio-technical security and usability, such as the visualization of personas as goal models to identify security tensions [8].

The analysis of GORE scientific production, when compared to the previous period (2016–2020) analyzed by Delima et al. [7], reveals stability in publication venues but significant transformations in the nature of contributions and supporting technologies.

Regarding publication channels, there is a clear continuity in the behavior of the academic community. Delima et al. [7] identified a near balance between journals (47.6%) and conference proceedings (52.4%). The current data (2021–2025) corroborate this trend, maintaining a statistically similar distribution of 53.52% for journals and 46.48% for conferences. This suggests that the community maintains a steady process of research maturation, in which conference papers evolve into journal publications, without a significant shift toward a single type of venue.

The most significant contrast lies in the contribution categories of the studies. In the previous period (2016–2020), Delima et al. [7] reported that most efforts (31.75%) focused on method improvement, particularly refining established languages such as i* and KAOS, while new approaches accounted for 26.98%.

In the current period (2021–2025), a substantial change toward innovation is observed: the "New Approach" category increased to 58% of total publications, becoming the dominant type of contribution. In contrast, "Method Development" decreased to 11%. This change suggests that the GORE community has shifted its focus from incremental refinement of classical notations to proposing new frameworks that integrate GORE with emerging paradigms. While the previous period emphasized language extensions, the current period emphasizes integration, particularly through the use of Large Language Models (LLMs) for model generation.

Delima et al. highlighted that, up to 2020, self-adaptive and socio-technical systems were the main application domains of GORE. While self-adaptive systems remain relevant, the 2021–2025 period shows an expansion toward Machine Learning (ML)-based systems and DevOps environments. The introduction of tools such as RV-SLC for DevOps validation and the extension of i* for ML-related requirements suggests that GORE has evolved beyond an early-phase activity to become an operational artifact. Unlike the 2016–2020 scenario, where automation was considered a future opportunity, the current landscape already offers concrete implementations enabled by generative AI.

These findings indicate that the evolution of GORE is no longer driven by internal methodological refinement, but by external technological pressures, particularly the rise of AI-based systems.

4.1 Synthesis of Findings

The results of this study suggest that GORE is undergoing a structural transformation rather than a gradual evolution. Traditionally centered on the refinement of modeling languages and formal methods, the field is now increasingly shaped by external technological drivers, particularly artificial intelligence [9] [24] [11].

This transformation changes GORE's role from a modeling-oriented discipline to an integrative layer within intelligent systems. Instead of focusing primarily on representation, recent approaches emphasize automation, adaptability, and interaction with runtime environments [2] [24] [6].

Furthermore, the growing use of Large Language Models (LLMs) introduces a fundamental change in how goal models are constructed and interpreted [5] [24], [6]. While traditional approaches rely on expert-driven modeling, generative techniques enable automated elicitation and reasoning, raising new challenges related to explainability, trust, and validation.

These findings indicate that the future of GORE lies not only in improving modeling techniques but in redefining its role as a bridge between human intentions and autonomous software systems.

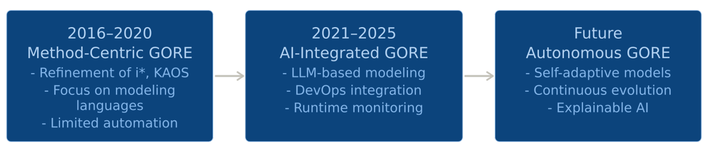

Fig. 6. Evolution of GORE from method-centric approaches to AI-driven integration.

Figure 6 summarizes this transformation, highlighting the transition from method-centric approaches to AI-integrated and future autonomous paradigms of GORE. The figure illustrates the conceptual evolution of GORE across three stages. The period from 2016 to 2020 is characterized by a focus on refining modeling languages and formal methods. From 2021 onward, GORE increasingly incorporates artificial intelligence techniques, particularly Large Language Models, enabling automation and integration with modern software engineering practices such as DevOps. Looking ahead, the field is expected to evolve toward autonomous GORE, where models continuously adapt and interact with runtime environments while maintaining explainability and alignment with stakeholder goals.

4.2 Research Gaps

The analysis reveals several important research gaps in the current GORE landscape.

First, there is a lack of validation frameworks for AI-generated goal models, particularly regarding explainability, trust, and correctness. While several studies propose automated model generation, few address how these models can be verified or validated in practice.

Second, the integration of GORE into DevOps environments remains limited, with few approaches addressing continuous evolution and maintenance of goal models in dynamic systems.

Third, there is no standardized approach for combining GORE with machine learning systems, particularly in defining goal alignment and handling uncertainty.

These gaps suggest important directions for future research.

4.3 Implications

The results indicate that GORE is increasingly integrating artificial intelligence and software engineering practices, while challenges related to trust, explainability, and workflow integration remain barriers to broader adoption.

4.4 Threats to Validity

This study presents some limitations. First, the search string “goal model” AND “requirement engineering” may exclude works using alternative terminology such as “goal-oriented requirements engineering”, narrowing the scope toward goal modeling rather than RE broadly. Second, the selection process may introduce bias despite the use of inclusion and exclusion criteria. Third, contribution classification involves subjective judgment, which may affect consistency. The screening and classification of studies were conducted by the five-member research team, with disagreements resolved by consensus. No artificial intelligence tools were used in any stage of the mapping process. Additionally, the search did not include manual searches in venues such as the iStar workshop, which may have resulted in the exclusion of relevant studies on i*-based modeling. Finally, the analysis is limited to four digital libraries, which may not cover the entire body of literature. The growing integration of GORE with AI techniques also emerged as an unpredicted trend; future studies may benefit from explicitly formulating a research question on this phenomenon.

5 Conclusion

This systematic mapping analyzed the state of the art of Goal-Oriented Requirements Engineering (GORE) between 2021 and 2025, serving as a direct and comparative update to the study conducted by Delima et al. [7] for the period from 2016 to 2020. The results suggest that GORE not only maintains its academic relevance, with stable publication patterns across conferences and journals, but is also undergoing a phase of technological and methodological renewal.

The most significant shift lies in the nature of contributions. While the previous period was marked by the predominance of method improvement (31.75%), focused on the incremental refinement of modeling languages, the current period consolidates the "New Approach" category (58%) as the dominant contribution type. This shift directly addresses the automation gap highlighted in the conclusions of Delima et al. [7], which emphasized the need to reduce dependence on human analysts.

This response from the scientific community has materialized in three main trends. First, the emergence of Generative GORE, where the use of *Large Language Models* (LLMs), such as GPT-4, for elicitation and automated modeling mitigates longstanding barriers related to complexity and manual effort [5] [9] [24]. Second, the field expands toward Runtime GORE, evolving from a purely early-stage design activity to integration with *DevOps* environments and continuous monitoring of critical and self-adaptive systems. Third, goal modeling assumes a central role in AI-based systems, providing a necessary layer of value alignment for Machine Learning applications.

In summary, while the period from 2016 to 2020 was characterized by the stabilization of notations, the period from 2021 to 2025 is defined by algorithmic integration. GORE has moved beyond its role as a static documentation tool to become a dynamic component of modern software engineering, driven by the incorporation of artificial intelligence models [6] [24] [2].

AI Usage Statement

The Grammarly tool was used exclusively for spelling and grammar checking, with no impact on the scientific content of the paper.

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