



Contents lists available at IJCHML  
International Journal of Computational Health and Machine  
Learning

Journal Homepage: <http://www.ijchml.com/>  
Volume 4, No. 1, 2023

**IJCHML**  
INTERNATIONAL JOURNAL OF  
COMPUTATIONAL HEALTH  
& MACHINE LEARNING

## Applications of Autoformalization in Scientific Research

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### ARTICLE INFO

Received: 10/23/2023

Revised: 11/21/2023

Accepted: 12/15/2023

#### Keywords:

autoformalization, scientific research, machine learning, formal methods, knowledge representation, automated reasoning, theorem proving

### ABSTRACT

The advent of autoformalization technologies, which aim to convert natural language descriptions into formal representations, has the potential to revolutionize scientific research by enhancing precision and facilitating automation. This paper explores the diverse applications of autoformalization across various scientific disciplines, highlighting its ability to streamline the formulation of hypotheses, automate the derivation of conclusions, and improve the reproducibility of scientific experiments.

Autoformalization enables researchers to bridge the gap between informal, human-readable scientific narratives and the rigorous, machine-interpretable formal languages used in computational models and proofs. By automatically translating complex theoretical constructs into formal systems, scientists can leverage computational tools to perform exhaustive analyses, thus expanding the scope of inquiry and enabling the discovery of novel insights that might otherwise remain obscured by the limitations of traditional research methodologies.

Furthermore, the integration of autoformalization into scientific workflows promotes the democratization of knowledge by reducing the barrier to entry for researchers who may lack extensive formal training in mathematical or logical frameworks. This fosters interdisciplinary collaboration and accelerates innovation by empowering a broader audience to contribute to complex problem-solving tasks. Additionally, the use of formalized representations ensures that scientific claims are articulated with unambiguous clarity, thereby reducing the potential for misinterpretation and enhancing the integrity of scientific communication.

In conclusion, autoformalization stands as a transformative force in the landscape of scientific research, offering unprecedented opportunities for automation, accuracy, and collaboration. As these technologies continue to evolve, their adoption promises to not only enhance the efficiency of existing research paradigms but also pave the way for new methodologies that harness the full potential of computational reasoning in the pursuit of scientific understanding.

## 1. Introduction

The advent of autoformalization in scientific research represents a significant paradigm shift, offering the

potential to revolutionize how complex problems are approached and solved. Autoformalization, the process by which informal natural language descriptions are transformed into formal, structured representations,

holds promise for enhancing the precision, reproducibility, and efficiency of scientific inquiry. As scientific research becomes increasingly intricate and data-driven, the demand for methodologies that can seamlessly bridge human intuition and formal logic grows ever more pressing. The utility of autoformalization lies in its ability to reduce human error, ensure consistency across research outputs, and streamline the integration of multidisciplinary insights.

The implementation of autoformalization tools facilitates the automatic generation and verification of formal proofs, the creation of mathematical models from textual descriptions, and the improvement of computational simulations. These capabilities provide researchers with robust frameworks to explore theoretical propositions, validate empirical data, and extrapolate findings across diverse scientific domains. The potential applications are vast, spanning fields such as mathematics, computer science, biology, and physics, each benefiting from the enhanced clarity and rigor that autoformalization affords. This paper seeks to explore these applications, drawing on recent advancements and examining the implications for future scientific endeavors.

### 1.1. Historical Context and Evolution of Autoformalization

The concept of autoformalization is deeply rooted in the broader field of artificial intelligence, which has long sought to emulate human cognitive processes through computational means. Early efforts in symbolic reasoning and automated theorem proving laid the groundwork for more sophisticated autoformalization techniques [2]. The development of formal languages and logic systems provided the necessary tools to represent complex ideas in a machine-readable format, enabling more advanced applications [3].

Over the past decade, significant strides have been made in natural language processing (NLP) and machine learning, further propelling the capabilities of autoformalization systems [9]. These advancements have facilitated the automatic translation of natural language into formal representations, making the process more accessible to non-experts and expanding its applicability across various scientific disciplines [13].

### 1.2. Methodologies and Techniques

The methodologies employed in autoformalization are multifaceted, often involving a combination of NLP, formal logic, and machine learning techniques. Key to this process is the development of robust algorithms capable of parsing and interpreting complex linguistic structures [7]. Machine learning models, particularly those based on neural networks, have been instrumental in improving the accuracy and efficiency of these

transformations [5].

Recent innovations have focused on enhancing the semantic understanding of text, allowing for more precise mappings between informal descriptions and their formal counterparts. Techniques such as semantic parsing and ontology-based reasoning are commonly used to disambiguate concepts and ensure logical consistency [10]. Moreover, the integration of domain-specific knowledge bases has proven essential in tailoring autoformalization tools to specific scientific fields [6].

### 1.3. Applications in Various Scientific Domains

The applications of autoformalization are diverse, with significant impacts observed across multiple scientific domains. In mathematics, autoformalization has been instrumental in automating the generation and verification of proofs, thereby accelerating the pace of discovery and reducing the likelihood of errors [8]. Similarly, in computer science, these techniques have facilitated the development of more efficient algorithms and software verification processes [1].

In the life sciences, autoformalization is employed to create detailed models of biological systems, enabling researchers to simulate complex interactions and predict outcomes with greater accuracy [11]. Physics and engineering have also benefited from these advancements, particularly in the modeling and simulation of intricate physical phenomena [4]. The versatility of autoformalization underscores its potential as a transformative tool in scientific research.

### 1.4. Challenges and Future Directions

Despite its promise, autoformalization faces several challenges that must be addressed to realize its full potential. One significant obstacle is the inherent complexity of natural language, which can lead to ambiguities and misinterpretations during the formalization process [12]. Additionally, the integration of autoformalization tools into existing research workflows requires careful consideration of usability and accessibility [2].

Future research must focus on developing more sophisticated models capable of handling the nuances of language and context across different scientific domains. Collaboration between linguists, computer scientists, and domain experts will be crucial in refining these tools and expanding their applicability [3]. As these challenges are overcome, the role of autoformalization in scientific research is poised to grow, offering unprecedented opportunities for innovation and discovery.

## 2. Related Work

The emergence of autoformalization techniques has significantly impacted various domains of scientific research, enabling researchers to automate the process of translating informal human knowledge into formal representations. This capability is particularly valuable in areas like mathematics, computer science, and the natural sciences, where rigorous formalization is crucial. The growing body of work in this field reflects diverse methodologies and applications, illustrating its potential to transform traditional research paradigms.

Autoformalization leverages advancements in artificial intelligence, particularly in natural language processing (NLP) and machine learning, to bridge the gap between human intuition and machine-readable formats. By automating the conversion of natural language descriptions into formal specifications, researchers can streamline the development of algorithms, improve the verification of scientific theories, and enhance collaborative efforts across disciplines. In this section, we present an overview of related work in autoformalization, structured into key thematic areas.

### 2.1. Mathematical Autoformalization

The application of autoformalization in mathematics has garnered considerable attention. Early efforts focused on translating mathematical texts into formal proofs, enabling automated theorem proving and verification. Notably, [2] explored the use of machine learning models to parse complex mathematical language, achieving significant improvements in theorem verification accuracy. Subsequent work by [3] applied deep learning techniques to enhance the scalability of these models, allowing for the formalization of more extensive mathematical corpora.

Recent advancements have further refined these techniques. For instance, [10] introduced a hybrid approach combining symbolic reasoning with neural networks, resulting in a more robust autoformalization pipeline. This methodology not only increased the accuracy of mathematical formalization but also reduced the computational resources required, thereby making it more accessible for widespread adoption.

### 2.2. Autoformalization in Computer Science

In computer science, autoformalization has been instrumental in software verification and the development of formal specifications. The work of [9] pioneered the use of autoformalization for generating formal specifications from natural language requirements, facilitating the verification process in software engineering. Building on this foundation, [7] demonstrated how autoformalization could be applied to derive executable code from informal

algorithm descriptions, thus bridging the gap between conceptual design and implementation.

Further contributions by [1] explored the integration of autoformalization with model checking techniques, significantly enhancing the reliability of concurrent systems. This integration enables the automated detection of inconsistencies between informal specifications and formal models, fostering more rigorous software development practices.

### 2.3. Interdisciplinary Applications

Beyond mathematics and computer science, autoformalization has found applications in a range of scientific disciplines. In the natural sciences, [13] highlighted the potential of autoformalization to formalize experimental protocols, thereby improving reproducibility and transparency in research. This approach was further expanded by [8], who applied autoformalization techniques to the domain of chemical engineering, automating the translation of process descriptions into formal reaction networks.

In the social sciences, [5] explored the use of autoformalization to formalize qualitative research findings, offering new possibilities for integrating qualitative and quantitative methodologies. This work emphasizes the transformative potential of autoformalization in fostering interdisciplinary research collaborations, as it provides a common formal framework for diverse scientific inquiries.

### 2.4. Challenges and Future Directions

Despite its potential, autoformalization faces several challenges, primarily related to the inherent complexity of natural language. As noted by [4], capturing the nuances and ambiguities of human language remains a significant hurdle. Furthermore, the work of [11] highlights the need for domain-specific adaptations of autoformalization techniques, as generic models often struggle with specialized terminologies and contexts.

Future research directions, as suggested by [6], include the development of more sophisticated models capable of handling context-dependent language features and the integration of domain knowledge to enhance model interpretability. Moreover, [12] advocates for the establishment of standardized benchmarks and datasets to facilitate the evaluation and comparison of autoformalization models across different domains.

In conclusion, the landscape of autoformalization research is rich with opportunities and challenges. Continued advancements in this field promise to further enhance the efficiency and accuracy of scientific research, ultimately leading to more robust and innovative outcomes across disciplines.

### 3. Methodology

Autoformalization, the process by which informal scientific concepts and hypotheses are translated into formal, machine-readable representations, has transformed the landscape of scientific research. The methodology of autoformalization involves a multi-step process that leverages advancements in natural language processing (NLP), formal logic, and machine learning (ML) to automate the conversion of natural language texts into formalized structures. This section details the methodological framework adopted for this study, which is designed to explore the applications of autoformalization in various scientific domains. The approach is structured into several phases, each critical to achieving a comprehensive understanding of autoformalization's potential and limitations.

The methodology is rooted in established frameworks that have been refined through recent advancements in AI and computational linguistics [2, 3, 9]. By building on these foundational works, our approach seeks to push the boundaries of autoformalization within the context of scientific inquiry, emphasizing the translation of complex scientific narratives into structured, computational forms.

#### 3.1. Data Collection

The initial phase of our methodology involves the systematic collection of scientific texts across a range of disciplines. This phase is crucial as it establishes the corpus from which autoformalization processes will be evaluated. Our dataset comprises peer-reviewed journal articles, conference papers, and technical reports from databases such as PubMed, IEEE Xplore, and ArXiv [7, 13]. The selection criteria for these texts were based on their relevance to key scientific domains, including biology, physics, and computer science.

To ensure the quality and diversity of the dataset, we employed stratified sampling techniques that allow for the inclusion of seminal works as well as recent advancements [5, 10]. The dataset was then pre-processed to remove extraneous elements such as bibliographies and appendices, focusing solely on the main body of text.

#### 3.2. Natural Language Processing and Pre-Processing

Once the dataset was established, the next phase involved the application of state-of-the-art NLP techniques to prepare the text for formalization. Tokenization, part-of-speech tagging, and syntactic parsing were performed using advanced NLP frameworks such as SpaCy and BERT [6, 8]. These tools facilitate the identification of key linguistic and structural features within the text.

Pre-processing also involved resolving anaphora and co-reference issues to ensure that all entities and concepts

within the text were clearly defined and disambiguated [1, 11]. This step is critical for reducing ambiguity in subsequent formalization processes, thus enhancing the accuracy of the autoformalization.

#### 3.3. Formalization Process

The core of our methodology is the formalization process, where pre-processed texts are converted into formal representations. This involves leveraging logic-based frameworks such as Description Logics (DL) and the Web Ontology Language (OWL), which are well-suited for representing complex scientific knowledge [4, 12]. The choice of formal language is pivotal, as it must balance expressiveness with computational tractability.

We utilized a hybrid approach that combines rule-based systems and machine learning algorithms to achieve high fidelity in formalization [3, 9]. Rule-based systems provide a structured framework for encoding domain-specific knowledge, while machine learning models offer the flexibility to generalize across various contexts.

#### 3.4. Evaluation and Validation

To assess the effectiveness of the autoformalization process, rigorous evaluation and validation techniques were employed. We adopted both qualitative and quantitative measures, including precision, recall, and F1-score metrics, to evaluate the accuracy of the formal representations against human expert annotations [2, 6].

Furthermore, validation was conducted by integrating the formalized knowledge into existing scientific reasoning systems and evaluating their performance on benchmark tasks [1, 7]. This step not only measures the accuracy of the formalization but also its utility in enhancing scientific discovery processes.

In conclusion, the methodology outlined here provides a comprehensive framework for exploring the applications of autoformalization in scientific research. By incorporating cutting-edge NLP and ML techniques, this approach aims to not only facilitate the automation of scientific formalization but also to enhance the precision and scope of scientific inquiry.

## 4. Results

The advent of autoformalization technologies has significantly transformed the landscape of scientific research. These technologies, which leverage advanced algorithms to convert informal scientific concepts into formalized mathematical expressions, have enabled researchers to enhance precision, reproducibility, and efficiency across various domains. By systematically structuring scientific knowledge, autoformalization facilitates deeper insights and paves the way for innovative applications. This

section delineates the results of applying autoformalization within scientific research, underscoring its myriad benefits and challenges.

Autoformalization has been instrumental in bridging the gap between qualitative intuition and quantitative rigor. By translating natural language descriptions into formal models, researchers can engage in more robust hypothesis testing and theory development [2, 3]. Moreover, these technologies promote interdisciplinary collaboration by providing a common formal language that is accessible across different scientific communities [9, 13].

#### 4.1. Enhancement of Reproducibility in Research

One of the primary applications of autoformalization has been in enhancing the reproducibility of scientific experiments. Reproducibility is a cornerstone of the scientific method, yet it remains a persistent challenge due to ambiguities in methodological descriptions [7]. Autoformalization addresses this challenge by converting narrative experimental procedures into formal protocols, which ensures that experiments can be replicated with high fidelity. Recent studies have shown significant improvements in reproducibility rates when autoformalization tools are employed, particularly in fields such as computational biology and materials science [5, 10].

#### 4.2. Facilitation of Automated Hypothesis Generation

Another pertinent application of autoformalization is in the facilitation of automated hypothesis generation. By formalizing existing data and theoretical frameworks, autoformalization tools can algorithmically generate plausible hypotheses that may not be immediately apparent to human researchers [6]. This capability has been particularly valuable in fields with large datasets, such as genomics and astronomy, where manual hypothesis generation is impractical [1, 8].

#### 4.3. Accelerating the Peer Review Process

The peer review process, a critical component of scientific validation, has also benefited from autoformalization. By providing a formal representation of research findings, reviewers can more efficiently evaluate the logical soundness and methodological rigor of submitted work [11]. This has led to a reduction in the time required for manuscript evaluations and has improved the overall quality of published research [4, 12].

### 4.4. Challenges and Limitations

Despite its advantages, the application of autoformalization is not without challenges. One significant limitation is the potential for over-reliance on formal models, which may overlook the nuanced understanding that qualitative analysis provides [6]. Additionally, the complexity of certain scientific domains may inhibit the development of comprehensive autoformalization tools that can accurately capture all relevant variables [10]. The ongoing refinement of algorithms and the integration of domain-specific knowledge are critical to addressing these challenges [3, 9].

In conclusion, the application of autoformalization technologies in scientific research has yielded substantial benefits, particularly in terms of reproducibility, hypothesis generation, and peer review efficiency. Nevertheless, the continuous evolution of these technologies and the careful consideration of their limitations are imperative to maximize their potential impact on the scientific community.

## 5. Discussion

In recent years, the advent of sophisticated machine learning models has facilitated the growth of autoformalization—a process by which informal scientific texts are translated into formal, machine-interpretable representations. This innovation holds promise for transforming scientific research by automating tedious aspects of formal modeling, enhancing reproducibility, and improving the accessibility of complex theoretical work. The discussion herein explores the current applications of autoformalization in scientific research, evaluating its impact and potential future directions.

Autoformalization is increasingly recognized as a pivotal tool in streamlining scientific workflows, particularly in domains heavily reliant on formal methods such as mathematics, computer science, and physics. By automating the translation of natural language into formal representations, researchers can more readily construct and verify models, thereby accelerating the pace of scientific discovery. However, the implementation of autoformalization also raises pertinent questions regarding its limitations, the accuracy of translations, and ethical considerations in its application.

#### 5.1. Enhancement of Scientific Workflow Efficiency

One of the most significant contributions of autoformalization is its ability to enhance the efficiency of scientific workflows. By automatically generating formal specifications from natural language descriptions, researchers can bypass the labor-intensive process of manual formalization. This is particularly beneficial

in fields such as software engineering, where formal specifications are critical for program verification and validation [2]. Studies have shown that autoformalization can reduce the time required to create formal models by up to 40% [4], thereby allowing scientists to allocate more resources to experimental and theoretical innovation.

Furthermore, the integration of autoformalization tools with existing research infrastructures can facilitate seamless transitions from hypothesis formulation to model testing and validation. For instance, in the realm of computational biology, autoformalization has been leveraged to rapidly develop formal models of complex biological systems, significantly reducing the time from data collection to hypothesis testing [3].

## 5.2. Improvement of Reproducibility in Research

Reproducibility is a cornerstone of scientific inquiry, yet it remains an elusive goal in many disciplines. Autoformalization can play a crucial role in addressing this challenge by providing clear, unambiguous representations of scientific theories and methodologies [9]. By translating informal descriptions into formal logic or mathematical equations, autoformalization ensures that analytical methods are transparent and replicable.

Moreover, the use of autoformalization can mitigate the risk of misinterpretation of scientific texts, which is a common barrier to reproducibility. As a result, autoformalization can lead to more robust scientific outcomes by ensuring that subsequent researchers can accurately replicate and validate findings [13].

## 5.3. Accessibility and Democratization of Complex Theoretical Work

The complexity of formal scientific language often restricts access to advanced theoretical work to a niche group of experts. Autoformalization has the potential to democratize access to scientific knowledge by providing more intuitive and accessible representations of complex theories [7]. This democratization can foster interdisciplinary collaboration, as researchers from diverse fields are better equipped to understand and apply advanced theoretical concepts.

For example, in the realm of theoretical physics, autoformalization tools have been used to create interactive models that enable non-specialists to explore complex phenomena without requiring extensive formal training [5]. This not only broadens the audience for scientific discourse but also encourages innovative approaches to problem-solving by incorporating diverse perspectives [10].

## 5.4. Challenges and Limitations

Despite its promising applications, autoformalization is not without challenges. One of the primary concerns is the accuracy and reliability of machine-generated formalizations. While advances in natural language processing have improved the fidelity of translations, there remain instances where nuances of human language are lost or misrepresented [6]. Such inaccuracies can lead to incorrect models or conclusions, thus underscoring the necessity for human oversight in the autoformalization process.

Additionally, ethical concerns arise regarding the potential for bias in machine learning models used for autoformalization. These biases can originate from the training data or the algorithms themselves, potentially leading to skewed formalizations that perpetuate existing biases or introduce new ones [8]. Addressing these ethical dimensions is critical to ensuring that autoformalization contributes positively to scientific progress without compromising integrity or equity.

## 5.5. Future Directions and Opportunities

The future of autoformalization in scientific research is rife with opportunities for innovation and expansion. As machine learning techniques continue to evolve, the precision and applicability of autoformalization tools are expected to improve [1]. Future research may focus on developing domain-specific autoformalization systems that cater to the unique requirements of different scientific fields. Additionally, integrating autoformalization with emerging technologies such as quantum computing could open new frontiers in computational efficiency and problem-solving capabilities [11].

Ultimately, the successful integration of autoformalization into scientific practice will depend on continued interdisciplinary collaboration, ethical vigilance, and a commitment to refining the tools and methods that underpin this transformative technology. By addressing these challenges and embracing future opportunities, autoformalization could become a cornerstone of modern scientific inquiry, reshaping how research is conducted and communicated [12].

## 6. Conclusion

The exploration of autoformalization in scientific research is a burgeoning field that holds immense promise for transforming how knowledge is generated, validated, and disseminated. This paper has investigated various applications of autoformalization, demonstrating its potential to enhance scientific rigor and efficiency across disciplines. By automating the process of converting

natural language descriptions into formal representations, researchers can bridge gaps between human intuition and machine precision, thereby fostering a more integrated approach to scientific inquiry [2, 3, 10].

As the scientific community continues to grapple with increasing data volumes and complexity, the role of autoformalization becomes even more critical. It offers a pathway not only to streamline research processes but also to enhance reproducibility and transparency in scientific reporting [9, 13]. This conclusion synthesizes the insights garnered from the investigation, underscoring the transformative impact of autoformalization on scientific research and outlining directions for future exploration.

### 6.1. Enhancing Research Efficiency and Accuracy

The application of autoformalization significantly reduces the burden of manual data processing and analysis, enabling researchers to focus on hypothesis generation and strategic decision-making. By automating the translation of complex ideas into formal systems, researchers can ensure greater accuracy in data interpretation and model building [1, 7]. This advancement not only accelerates the research lifecycle but also minimizes human errors, which are often prevalent in manual data handling processes [6].

Moreover, autoformalization facilitates the seamless integration of interdisciplinary knowledge, allowing for more holistic and innovative approaches to problem-solving. As the boundaries between scientific domains become increasingly porous, the capacity to automatically formalize and interconnect diverse data sets and theoretical frameworks becomes a pivotal asset [4, 5].

### 6.2. Improving Reproducibility and Transparency

One of the most profound impacts of autoformalization is its potential to enhance reproducibility, a cornerstone of scientific progress. By providing a precise, machine-readable format for scientific claims and methodologies, autoformalization ensures that research findings can be easily verified and replicated by other scholars [8, 11]. This capability addresses a critical challenge in contemporary science, where the reproducibility crisis has raised questions about the reliability of many published results [12].

Furthermore, the transparency afforded by autoformalization means that the underlying assumptions and logical structures of research can be scrutinized and critiqued with unprecedented clarity. This openness not only fosters trust among researchers but also encourages more rigorous peer review processes, ultimately leading to

higher-quality scientific outputs [6, 10].

### 6.3. Future Directions and Challenges

Despite its promising applications, the widespread adoption of autoformalization in scientific research is not without challenges. The development of robust algorithms capable of accurately interpreting and formalizing the nuanced language of science remains a significant hurdle [1, 13]. Moreover, interdisciplinary collaboration is essential to refine these tools, requiring concerted efforts from computer scientists, domain experts, and linguists alike [3, 4].

Looking ahead, future research should focus on creating more sophisticated autoformalization frameworks that can accommodate the diverse and complex nature of scientific inquiry. Additionally, ethical considerations related to data privacy and the potential for bias in automated systems must be addressed to ensure the responsible use of these technologies [2, 7].

In conclusion, the applications of autoformalization in scientific research represent a paradigm shift with the potential to fundamentally alter the landscape of science. As the technology continues to evolve, it will undoubtedly enrich the scientific endeavor, driving innovation and discovery across fields [8, 12].

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