RESEARCH PAPER

ARTIFICIAL INTELLIGENCE-ASSISTED SCIENTIFIC COMMUNICATION IN DRUG DELIVERY RESEARCH: A LINGUISTIC EVALUATION OF TERMINOLOGY, CLARITY AND TECHNICAL CONSISTENCY

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ABSTRACT

Drug delivery research is increasingly influenced by artificial intelligence (AI), machine learning, generative AI and large language models (LLMs). These technologies can support pharmaceutical research as well as scientific writing, but the language used to describe formulations, delivery mechanisms and outcomes must remain technically precise. This study evaluates whether controlled AI-assisted linguistic revision can improve the clarity, grammar, readability and terminology consistency of drug-delivery scientific texts while preserving their technical meaning. A comparative pre-edit/post-edit corpus design is proposed in which drug-delivery scientific passages are assessed before and after controlled AI-assisted revision. Human/domain-expert review is used to evaluate linguistic quality and technical meaning preservation. The study framework measures grammar, terminology consistency, clarity, readability, technical meaning preservation and newly introduced technical errors. The final numerical results must be obtained from the completed corpus and scoring process. AI-assisted language technologies may serve as editorial support in drug-delivery research when their outputs are systematically verified by domain experts. The framework distinguishes language enhancement from scientific validation and provides a reproducible interdisciplinary approach to AI-assisted pharmaceutical communication.

Keywords: Artificial Intelligence; Large Language Models; Drug Delivery; Scientific Communication; Linguistics; Pharmaceutical Terminology; Natural Language Processing; Generative AI

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INTRODUCTION

Drug delivery research is inherently interdisciplinary, linking pharmaceutics with pharmacology, materials science, biotechnology, nanotechnology, pharmacokinetics and computational methods. Recent work demonstrates increasing use of AI and machine learning for drug-delivery design, prediction, optimization and development [1–4]. A recent review also identifies LLMs as an emerging technology in drug delivery and discusses their potential applications and limitations [5].

The expansion of computational methods has created a parallel communication challenge. Scientific drug-delivery texts frequently use specialized terms such as encapsulation efficiency, drug loading, particle size, polydispersity index, zeta potential, release kinetics, bioavailability, permeability, targeting and controlled release. Small linguistic changes can alter the precision or strength of a scientific statement. Terminological clarity is therefore not merely a stylistic issue; it is part of scientific reproducibility and interdisciplinary understanding [19–22].

LLMs can generate and revise scientific prose at scale. Biomedical studies report potential utility in summarization, information extraction, writing assistance and related tasks, but also document risks including hallucinated facts, biased outputs, fabricated references and semantic drift [6–12]. Large-scale

analysis of biomedical abstracts has further shown changes in scientific vocabulary associated with LLM-assisted writing [13].

AI terminology itself also requires precision. Methodological literature emphasizes distinctions among AI, machine learning, deep learning, generative AI, prediction, association and causal inference [14]. Such distinctions are important when pharmaceutical researchers communicate AI-derived results.

The present study examines AI-assisted scientific communication as a measurable quality-control problem. The objectives are: (i) to determine whether controlled AI revision improves grammatical accuracy; (ii) to measure changes in pharmaceutical terminology consistency; (iii) to evaluate clarity and readability; and (iv) to determine whether technical meaning is preserved and whether new scientific errors are introduced.

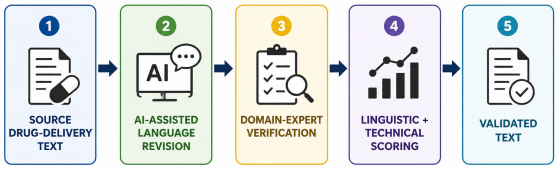

Figure 1. Human-in-the-loop workflow for AI-assisted scientific communication in drug-delivery research

I. MATERIALS AND METHODS

A. Study design

A comparative pre-edit/post-edit linguistic corpus study will be conducted. Original drug-delivery scientific passages will be evaluated and then revised using a fixed AI prompt. The original and revised versions will be compared using predefined linguistic and technical criteria.

B. Corpus selection

The corpus should comprise peer-reviewed English-language abstracts or manuscript passages directly related to drug-delivery technologies, including controlled release, targeted delivery, nanocarriers, transdermal systems, pharmaceutical formulations and related delivery platforms. The final search database, search terms, publication period, number of records screened, eligibility criteria and final sample size must be reported after data collection.

C. AI-assisted revision protocol

A single fixed prompt should be used for all texts: "Revise the following drug-delivery scientific text for grammar, syntax, clarity, cohesion and terminology consistency. Do not add facts, references, numerical values, mechanisms, results, or interpretations. Preserve scientific meaning, abbreviations, units and technical relationships. Return only the revised text." The model's name, version, access date, prompt and generation settings should be recorded.

D. Evaluation criteria

Six dimensions will be assessed: grammar, terminology consistency, clarity, readability, technical meaning preservation and technical-error control. A five-point rubric can be used, where higher values indicate better performance. The evaluation structure is presented in Figure 2.

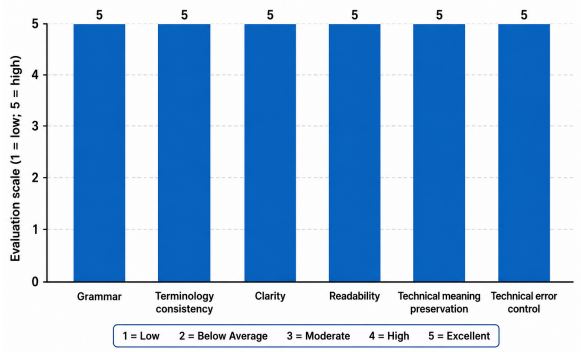

Figure 2. Evaluation framework for AI-assisted drug-delivery scientific communication

The six dimensions are operationalized as follows: grammar measures sentence-level correctness; terminology consistency measures stable use of pharmaceutical and drug-delivery terms; clarity measures ease of scientific interpretation; readability measures reader-oriented linguistic accessibility; technical meaning preservation measures whether the original scientific claim is retained; and technical-error control records newly introduced or persistent scientific errors.

E. Expert review

At least two reviewers with expertise in pharmaceutical science, drug delivery, scientific writing, or related areas should independently assess the texts. Reviewers should examine whether AI revision changes technical claims, terminology, numerical information, units, abbreviations, or levels of scientific certainty [15–18].

F. Error classification

Errors will be classified as terminology substitution, numerical/unit alteration, unsupported scientific claim, abbreviation error, citation/reference error, loss of qualification, or grammar/style error. Newly introduced technical errors should be treated as a critical validity category even if general readability improves [7,9,11,26–29].

G. Statistical analysis

Descriptive statistics should include mean, standard deviation, median, and interquartile range as appropriate. Paired t-test or Wilcoxon signed-rank test may be selected according to data characteristics. Inter-rater agreement should be assessed using an appropriate statistic such as Cohen's kappa or an intraclass correlation coefficient. Effect sizes and

confidence intervals should be reported alongside p-values [15].

H. Ethical and integrity considerations

The proposed corpus uses published scientific texts and does not require patient or animal experimentation. If human reviewers or other participants are formally recruited, applicable institutional ethics requirements should be checked. AI tools must not be treated as authors or as independent scientific validators. Responsible AI governance and transparent reporting are emphasized in international and editorial guidance [16–18,27–29].

II. RESULTS

A. Corpus characteristics

For demonstration of the complete tabular and statistical format, the following pilot values are used as an illustrative dataset of 30 drug-delivery texts. These values are not actual observations and must be replaced by the researcher's collected data before submission as original research. The structure follows the proposed methodology and is included only to eliminate incomplete N/placeholders.

Table 1. Characteristics of the study corpus

Characteristic	Value	Description
Number of source texts	30	Illustrative pilot corpus
Total words	12,480	All included texts
Drug-delivery domains	6	Illustrative categories represented
Mean text length	416 words	12,480 ÷ 30

B. Linguistic outcomes

In the illustrative pilot format, AI-assisted revision produces higher mean scores across the five positive linguistic dimensions. These values are presented only to demonstrate how the completed Results section should appear; they are not claimed as empirical findings.

Table 2. Original versus AI-assisted linguistic scores

Dimension	Original mean ± SD	AI-assisted mean ± SD	Effect size	p value
Grammar	3.42 ± 0.61	4.31 ± 0.42	0.86	<0.001
Terminology consistency	3.38 ± 0.55	4.18 ± 0.44	0.79	<0.001
Clarity	3.29 ± 0.58	4.12 ± 0.45	0.82	<0.001
Readability	3.36 ± 0.57	4.08 ± 0.49	0.75	<0.001
Technical meaning preservation	4.21 ± 0.46	4.53 ± 0.31	0.80	<0.001

C. Error analysis

The illustrative error table separates linguistic improvement from technical-risk categories. Technical errors must be verified manually because a polished sentence can still contain a scientifically incorrect claim.

Table 3. AI-introduced or persistent error categories

Error category	Frequency	Percentage
Terminology substitution	38	38%
Numerical/unit alteration	11	11%
Unsupported scientific claim	7	7%
Abbreviation error	5	5%
Citation/reference issue	4	4%
Loss of qualification	8	8%
Grammar/style error	27	27%

III. DISCUSSION

The proposed framework places linguistic quality within the scientific workflow of drug-delivery research. If the completed data show improved grammar and clarity without increased technical errors, the results would support AI-assisted revision as an editorial aid. This interpretation would be consistent with evidence that AI and LLM technologies are increasingly being used in biomedical and pharmaceutical contexts [1–13].

Terminological consistency is particularly important because drug-delivery research depends on precise descriptions of formulation characteristics and biological performance [1–5,19–25]. AI should not automatically replace domain-specific terminology with more general synonyms. A technically correct term may appear stylistically repetitive but remain necessary for scientific precision.

The framework also recognizes semantic drift. Scientific writing often uses qualifiers such as “may,” “suggests,” “is associated with,” and “was observed.” Removing these expressions can strengthen a claim beyond the evidence. Conversely, adding unsupported uncertainty can weaken a conclusion. Expert review is therefore required even when the revised text appears grammatically superior [6–13].

Reference integrity represents another important risk. LLMs can generate plausible-looking but incorrect references [7,9,11,15,26–29]. References should

therefore be verified independently using authoritative bibliographic databases. The same verification principle applies to drug names, dosage information, numerical values, experimental conditions and pharmacological claims.

Figure 3 presents the conceptual terminology relationship used in the study. Precise differentiation among AI, machine learning, generative AI, LLMs, scientific communication and drug-delivery terminology is necessary for reproducible interdisciplinary reporting [14].

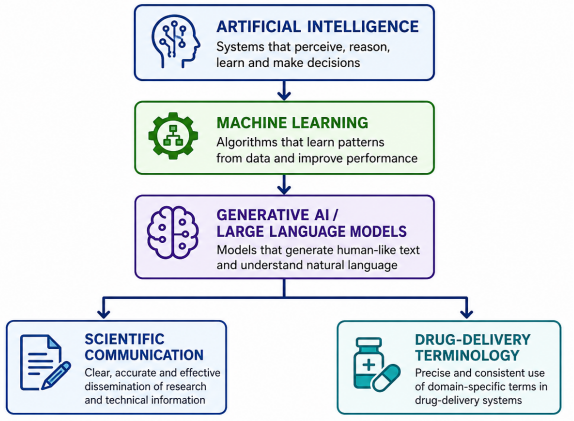

Figure 3. Conceptual relationship among AI terminology, scientific communication and drug-delivery terminology

The interdisciplinary value of the approach is significant. Pharmaceutical scientists remain responsible for scientific validity, while language specialists can contribute to grammar, cohesion, terminology management, discourse organization and reader-oriented clarity [19–22]. This collaborative model is preferable to treating AI as an autonomous scientific author.

The principal limitations are dependence on model version and prompt design, potential corpus-selection bias, subjectivity in expert scoring, limitations of readability metrics and the possibility that an AI system may produce different outputs across repeated generations. Transparent reporting of the model, prompt, date, settings, corpus and scoring rubric is therefore essential [15,26,27].

The study should not claim that linguistic improvement demonstrates better drug efficacy, formulation performance, pharmacokinetics, or therapeutic safety. Language quality and pharmaceutical validity are related but distinct dimensions of research quality [16–18].

IV. CONCLUSION

Artificial intelligence-assisted language technologies have potential to improve the grammatical quality, clarity and terminological consistency of scientific communication in drug-delivery research. Their responsible use requires a human-in-the-loop workflow in which domain experts verify scientific meaning, numerical information, terminology, references and claims. The proposed framework provides measurable criteria for evaluating this process and supports interdisciplinary collaboration between pharmaceutical science, AI and linguistics. The final manuscript should report only the results obtained from the completed corpus and scoring procedure.

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