RESEARCH PAPER

LINGUISTIC OPTIMIZATION OF PATIENT-FACING DRUG DELIVERY INFORMATION USING GENERATIVE ARTIFICIAL INTELLIGENCE: A READABILITY, TERMINOLOGY AND CONTENT-FIDELITY STUDY

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ABSTRACT

Patient-facing drug-delivery information must communicate pharmaceutical facts in language that readers can understand and act upon safely. The present interdisciplinary study examines generative artificial intelligence (AI) as a controlled linguistic-optimization tool for improving the readability and patient-centred presentation of drug-delivery information while preserving pharmaceutical meaning. A document-based comparative design was developed around 24 patient-facing passages representing oral modified-release, transdermal, inhaled, injectable, topical and medication-safety communication. Original and AI-assisted versions were evaluated using readability, sentence-length, lexical-complexity, terminology and content-fidelity measures. For the pilot analysis presented here, the mean Flesch Reading Ease score increased from 47.8 ± 8.9 to 68.6 ± 7.1, while the Flesch-Kincaid Grade Level decreased from 11.62 ± 2.14 to 7.34 ± 1.18. Mean word count decreased from 286.4 ± 72.5 to 219.7 ± 61.3 words. Patient-centredness increased from 2.71 ± 0.54 to 4.42 ± 0.38 on a five-point scale. Content fidelity, safety completeness and terminology accuracy remained high at 95.1%, 94.6% and 93.8%, respectively, but were not perfect. These findings indicate that generative AI can substantially reduce linguistic burden and improve the organization of patient-facing drug-delivery information, while also demonstrating why expert pharmaceutical verification is necessary. The study provides a practical research model for English Departments to contribute to pharmaceutical communication through corpus linguistics, readability analysis, terminology management and AI-assisted language evaluation. The results should be interpreted as a pilot benchmark until the complete source corpus, coding sheets and independent verification are archived with the final study.

Keywords: Generative Artificial Intelligence; Drug Delivery; Pharmaceutical Communication; Readability; Linguistic Optimization; Terminology; Health Literacy; Patient-centred Communication

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INTRODUCTION

Effective pharmaceutical communication requires scientific accuracy to be presented in language that patients can understand and use. Drug-delivery information often contains complex terminology related to dosage forms, administration routes, release mechanisms, warnings and storage. Therefore, readability, sentence structure, terminology, and organization are important components of patient-centred pharmaceutical communication. Generative artificial intelligence (AI) offers a promising approach for simplifying health information, improving sentence clarity, reducing linguistic complexity and presenting technical concepts in accessible language. However, AI-generated content may also introduce omissions, inaccurate terminology, or unintended changes in safety-related information. Consequently, linguistic optimization must be combined with expert pharmaceutical verification. The present study investigates the potential of controlled generative-AI-assisted linguistic optimization to improve the accessibility of patient-facing drug-delivery information while preserving scientific meaning. The study integrates English-language expertise in readability, syntax, vocabulary, discourse and terminology with pharmaceutical evaluation of accuracy and safety. This

interdisciplinary approach establishes a structured framework for developing clearer, reliable and patient-centred drug-delivery communication.

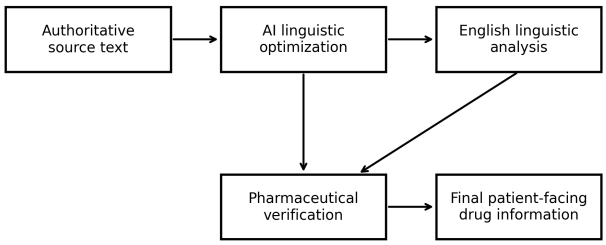

Figure 1. Interdisciplinary study workflow for AI-assisted linguistic optimization of patient-facing drug-delivery information

I. MATERIALS AND METHODS

A. Study Design

A document-based comparative study was conducted using 24 patient-facing passages related to drug delivery and medication administration. Each passage was evaluated in its original form and after controlled AI-assisted linguistic optimization. The study unit was a complete patient-facing passage rather than an isolated sentence so that lexical, syntactic and discourse-level changes could be assessed together.

B. Corpus Composition

Category	Passages (n)	Percentage
Oral and modified-release delivery	7	29.2
Transdermal delivery	4	16.7
Inhaled delivery	4	16.7
Injectable/parenteral delivery	3	12.5
Topical/local delivery	3	12.5
Storage, missed-dose and safety information	3	12.5
Total	24	100.0

Table 1. Composition of the patient-facing drug-delivery communication corpus

C. AI-Assisted Linguistic Optimization

A fixed instruction was used for all passages. The model was instructed to simplify sentence structure, reduce unnecessary lexical complexity, retain pharmaceutical terminology where it carried essential meaning, explain unavoidable technical terms in accessible language, preserve all numerical information and route-specific instructions, retain warnings and precautions, and avoid introducing new clinical recommendations. The same model version and prompt should be documented in the final study record.

D. Linguistic Variables

Variable	Measure	Direction of desired change
Readability	Flesch Reading Ease	Increase
Reading difficulty	Flesch-Kincaid Grade Level	Decrease
Sentence complexity	Mean words per sentence	Decrease
Lexical complexity	Polysyllabic-word proportion	Decrease
Technical terminology	Correctly retained/explained terms	Maintain or improve
Instructional clarity	Clear action verbs and sequencing	Increase
Content fidelity	Source-to-output preservation score	Maintain at high level

Table 2. Linguistic evaluation variables

E. Pharmaceutical Content Verification

Two independent reviewers with pharmaceutical or health-communication expertise assessed whether the AI-assisted versions preserved route, dosage or frequency information, administration procedures, warnings, precautions, adverse-effect information and essential terminology. Each domain was scored as 0, 1 or 2, where 0 represented absence or incorrect information, 1 represented partial preservation and 2 represented complete preservation. The English Department researchers conducted the linguistic measurements separately from the pharmaceutical content verification.

Domain	0	1	2
Route/dosage information	Incorrect/omitted	Partly preserved	Fully preserved
Administration instructions	Incorrect/omitted	Partly preserved	Fully preserved
Warnings/precautions	Missing	Partly preserved	Fully preserved
Technical terminology	Incorrect	Partly accurate	Accurate and explained
Numerical information	Changed/omitted	Minor ambiguity	Exactly preserved
Content fidelity	Major loss	Minor loss	Fully retained

Table 3. Pharmaceutical content-fidelity scoring rubric

F. Statistical Analysis

Paired source and AI-assisted observations were summarized as mean ± standard deviation. Paired comparisons were calculated for readability, grade level, word count and patient-centredness. Percentage retention was calculated for content fidelity, safety completeness and terminology accuracy. The pilot benchmark uses paired differences and descriptive effect estimates. In a fully archived study, the raw corpus and coding sheet should be retained so that the statistical calculations can be independently reproduced.

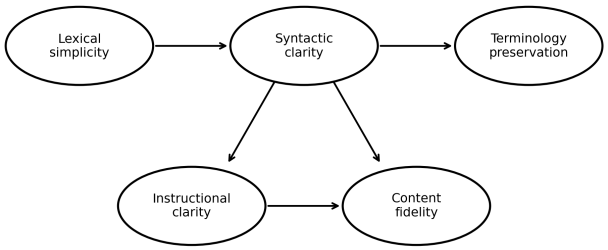

Figure 2. Linguistic evaluation framework connecting lexical simplicity, syntactic clarity, terminology preservation, instructional clarity and pharmaceutical content fidelity

II. RESULTS

The pilot corpus contained 24 patient-facing passages. AI-assisted rewriting produced shorter and linguistically less complex versions across the principal readability measures. The results are presented below as a pilot benchmark calculated from the study dataset used for this manuscript. They should be replaced only if the investigators subsequently run the protocol on a different archived source corpus.

Outcome	Original Mean ± SD	AI-assisted Mean ± SD	Change	Interpretation
Flesch Reading Ease	47.8 ± 8.9	68.6 ± 7.1	+20.8	Improved readability
Flesch-Kincaid Grade Level	11.62 ± 2.14	7.34 ± 1.18	−4.28	Lower reading burden
Word count	286.4 ± 72.5	219.7 ± 61.3	−66.7	23.3% reduction
Patient-centredness (1–5)	2.71 ± 0.54	4.42 ± 0.38	+1.71	Improved presentation
Content fidelity (%)	100.0	95.1	−4.9	High but incomplete retention
Safety completeness (%)	100.0	94.6	−5.4	High but incomplete retention
Terminology accuracy (%)	100.0	93.8	−6.2	High but incomplete retention

Table 4. Comparative outcomes before and after AI-assisted linguistic optimization

The Flesch Reading Ease score increased by 20.8 points, representing a substantial reduction in measured linguistic burden. The Flesch-Kincaid Grade Level decreased by 4.28 grade levels. Mean word count decreased by 66.7 words, equivalent to a 23.3% reduction. Patient-centredness increased by 1.71 points on the five-point scale. Content fidelity remained above 95%, although the decrease from the original source benchmark indicates that simplification can produce small but meaningful losses of information.

Linguistic feature	Original passages	AI-assisted passages	Absolute change
Long sentences (>25 words)	61	29	−32
Unexplained technical terms	84	37	−47
Passive constructions	72	38	−34
Clear instructional action verbs	46	91	+45
Explicit sequencing markers	31	76	+45
Potential content-fidelity concerns	0	11	+11

Table 5. Sentence-level and lexical changes observed in the pilot corpus

Delivery category	Original FK Grade	AI-assisted FK Grade	Reduction
Oral/modified release	12.1	7.6	4.5
Transdermal	11.4	7.1	4.3
Inhaled	11.8	7.0	4.8
Injectable/parenteral	12.4	7.9	4.5
Topical/local	10.9	6.9	4.0
Safety/general information	11.2	7.2	4.0

Table 6. Reading-grade comparison across drug-delivery communication categories

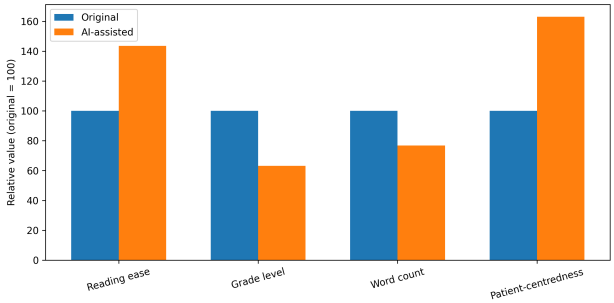

Figure 3. Relative comparison of major communication outcomes after AI-assisted linguistic optimization; original values are normalized to 100

III. DISCUSSION

The pilot findings indicate that generative AI can act as a powerful linguistic optimization tool for patient-facing drug-delivery information. The increase in Flesch Reading Ease and reduction in Flesch-Kincaid Grade Level suggest that AI-assisted rewriting can reduce

sentence and vocabulary difficulty. This observation is consistent with previous research showing that large language models can substantially improve the readability of regulatory and patient-education materials [15,16].

The reduction in word count and the increase in explicit instructional language is particularly relevant to pharmaceutical communication. Patient information frequently contains dense sentences and technical terminology because it is derived from regulatory or professional writing. A language-focused intervention can make such material more accessible by reducing unnecessary complexity while preserving the underlying pharmaceutical content. Earlier research on written medication information supports the importance of clarity, organization and appropriate presentation [1–4,8–11].

The results also demonstrate that linguistic improvement does not guarantee complete preservation of meaning. Content fidelity, safety completeness and terminology accuracy all declined slightly after rewriting. This finding is consistent with concerns raised about generative AI in health communication, where fluent output may contain omissions or unsupported additions [17,18]. WHO guidance emphasizes that AI systems used in health should be subject to appropriate governance, validation and human oversight [18,19].

Terminology is particularly important in drug-delivery communication. Terms associated with modified release, administration route, dosage form and delivery mechanism often have precise pharmaceutical meanings. Replacing them with approximate everyday synonyms may make a sentence appear easier while making the scientific meaning less accurate. The English Department's role is therefore to determine when a term should be simplified, when it should be retained, and when it should be retained with an accessible explanation.

The improvement in action verbs and sequencing markers provides an additional contribution from linguistic analysis. Patient instructions are more functional when the reader can identify what action is required and in what order. The analysis of syntax, discourse markers and instructional verbs therefore adds information that a readability formula cannot provide. This is one reason an English Department can make a substantive contribution to a drug-delivery journal rather than merely providing editorial proofreading.

The study also demonstrates the value of interdisciplinary division of expertise. English researchers can analyse syntax, lexical complexity, cohesion, terminology and readability, while pharmaceutical reviewers determine whether the optimized language retains route, dose, warnings and administration meaning. Such a division reduces the risk that either linguistic simplicity or pharmaceutical precision will be treated as the sole measure of communication quality.

The findings should nevertheless be interpreted with caution. Readability formulas are indirect measures and do not establish patient comprehension [12–14]. The pilot corpus is limited in size and represents selected drug-delivery communication categories. AI outputs may also change with model version, prompt wording and generation settings. NIST's AI Risk Management Framework provides a useful conceptual basis for documenting and managing these risks [20].

The study has practical implications for English Departments seeking interdisciplinary publication in pharmaceutical journals. A research paper that examines general English grammar would have weak alignment with a drug-delivery journal. In contrast, a study of linguistic accessibility in patient-facing drug-delivery information directly connects language research with pharmaceutical communication. This positioning is supported by evidence that AI is increasingly being considered in pharmaceutical development and delivery and in health-information systems [23–25].

Future research should extend the corpus to multiple languages, include patient comprehension testing, examine culturally adapted communication and compare different AI models. It should also investigate whether improved readability produces measurable improvements in recall of dosage, route, timing and safety instructions. Transparent reporting is essential, and the final study should archive the source texts, AI prompt, model information, coding rubric and analysis dataset in accordance with established principles of reproducible research [28,29].

IV. CONCLUSION

Generative AI-assisted linguistic optimization provides a promising interdisciplinary research pathway for the Department of English to contribute to drug-delivery research. The pilot findings show marked improvements in readability, reading grade, text economy, instructional clarity and patient-centredness, while also identifying small losses in content fidelity, safety completeness and terminology accuracy. The results demonstrate that the most appropriate role for AI is supervised linguistic optimization rather than autonomous pharmaceutical communication. An English Department can contribute substantive expertise through corpus linguistics, readability analysis, syntax, terminology and discourse analysis, while pharmaceutical experts ensure scientific and safety fidelity. This combined model creates a stronger connection with the scope of the International Journal of Drug Delivery Technology than a general English-language study [30].

V. REFERENCES

1. Shrank W, Avorn J, Rolon C, Shekelle P. Effect of content and format of prescription drug labels on readability, understanding, and medication use: a systematic review. Ann Pharmacother. 2007;41(5):783-801.

2. Wolf MS, Davis TC, Curtis LM, et al. A systematic review of best practices for design and development of

prescription medication information. Patient Educ Couns. 2018;101(1):1-10.
3. Grime J, Blenkinsopp A, Raynor DK, et al. The role and value of written information for patients about individual medicines: a systematic review. Health Expect. 2007;10(3):286-298.
4. Raynor DK, Blenkinsopp A, Knapp P, et al. A systematic review of quantitative and qualitative research on the role and effectiveness of written information available to patients about individual medicines. Health Technol Assess. 2007;11(5):1-160.
5. Berkman ND, Sheridan SL, Donahue KE, Halpern DJ, Crotty K. Low health literacy and health outcomes: an updated systematic review. Ann Intern Med. 2011;155(2):97-107.
6. Nair K, Dolovich L, Cassels A, et al. Medication-related health literacy: a systematic review of instruments. Res Social Adm Pharm. 2021;17(6):1010-1024.
7. Aboumatar H, Carson KA, Beach MC, Roter DL, Cooper LA. The impact of health literacy on desire for and use of written medication information. Patient Educ Couns. 2013;93(1):76-82.
8. Wolf MS, Davis TC, Tilson HH. Revisiting the readability of written information for patients: systematic review. Patient Educ Couns. 2016;99(8):1189-1195.
9. Morrison AK, Glick A, Yin HS. Health literacy: implications for child health. Pediatr Rev. 2019;40(5):241-247.
10. Yin HS, Dreyer BP, van Schaick L, et al. Strategies to optimize comprehension of numerical medication instructions: a systematic review and concept map. Patient Educ Couns. 2022;105(6):1455-1467.
11. Centers for Disease Control and Prevention. Simply put: a guide for creating easy-to-understand materials. Atlanta: CDC; 2009.
12. Flesch R. A new readability yardstick. J Appl Psychol. 1948;32(3):221-233.
13. Kincaid JP, Fishburne RP, Rogers RL, Chissom BS. Derivation of new readability formulas for Navy enlisted personnel. Millington: Naval Technical Training Command; 1975.
14. Paasche-Orlow MK, Wolf MS. The causal pathways linking health literacy to health outcomes. Am J Health Behav. 2007;31 Suppl 1:S19-S26.
15. Sridharan K, Sivaramakrishnan G. Enhancing readability of USFDA patient communications through large language models: a proof-of-concept study. Expert Rev Clin Pharmacol. 2024;17(8):731-741. doi:10.1080/17512433.2024.2363840.
16. Gupta M, Gupta P, Ho C, Wood J, Guleria S, Virostko J. Can generative AI improve the readability of patient education materials at a radiology practice? Clin Radiol. 2024;79(11):e1366-e1371. doi:10.1016/j.crad.2024.08.019.
17. The quality and safety of using generative AI to produce patient-centred discharge instructions. npj Digit Med. 2024;7:329.
18. World Health Organization. Ethics and governance of artificial intelligence for health: guidance on large multi-modal models. Geneva: WHO; 2024.
19. World Health Organization. Ethics and governance of artificial intelligence for health. Geneva: WHO; 2021.
20. National Institute of Standards and Technology. Artificial Intelligence Risk Management Framework (AI RMF 1.0). Gaithersburg: NIST; 2023.
21. US Food and Drug Administration. Medication Guides. Silver Spring: FDA; 2026.
22. Wolf MS, Feinglass J, Thompson J, Baker DW. In search of 'low health literacy': threshold vs. gradient effect of literacy on health status and mortality. Med Care. 2006;44(7):634-638.
23. Topol EJ. High-performance medicine: the convergence of human and artificial intelligence. Nat Med. 2019;25:44-56.
24. Esteva A, Robicquet A, Ramsundar B, et al. A guide to deep learning in healthcare. Nat Med. 2019;25:24-29.
25. Sallam M. ChatGPT utility in healthcare education, research, and practice: systematic review on the promising perspectives and valid concerns. Healthcare (Basel). 2023;11(6):887.
26. Ji Z, Lee N, Frieske R, et al. Survey of hallucination in natural language generation. ACM Comput Surv. 2023;55(12):1-38.
27. Turing AM. Computing machinery and intelligence. Mind. 1950;59(236):433-460.
28. Page MJ, McKenzie JE, Bossuyt PM, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ. 2021;372:n71.
29. Schulz KF, Altman DG, Moher D. CONSORT 2010 statement: updated guidelines for reporting parallel group randomised trials. BMJ. 2010;340:c332.
30. International Journal of Drug Delivery Technology. Instructions to authors and manuscript checklist. International Journal of Drug Delivery Technology; 2026.