RESEARCH PAPER

DISCOURSE ENGINEERING OF PATIENT INSTRUCTIONS FOR ADVANCED DRUG DELIVERY: AN ENGLISH-LANGUAGE FRAMEWORK FOR AI-ASSISTED MEDICATION ADHERENCE COMMUNICATION

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ABSTRACT
Effective drug-delivery communication depends not only on readability but also on whether instructions clearly communicate what the patient should do, when the action should occur, what precautions apply, and how the patient can respond to uncertainty. This study proposes and evaluates a discourse-engineering framework for converting patient-facing drug-delivery instructions into structured AI-assisted medication-adherence dialogues. Unlike conventional readability studies, the investigation focuses on discourse functions, action sequencing, temporal expressions, warning prominence, clarification prompts and adherence-oriented language. A pilot corpus of 30 drug-delivery instruction units was segmented into five discourse functions: instructional, temporal, safety, adherence and clarification. Each unit was transformed into a controlled dialogue prototype and independently rated for communication performance. In the pilot benchmark, mean ratings increased from 2.7 to 4.3 for action clarity, 2.5 to 4.2 for sequence clarity, 2.8 to 4.1 for warning visibility, 2.6 to 4.0 for terminology support and 2.4 to 4.2 for adherence orientation on a five-point scale. The framework preserves pharmaceutical information while reorganizing language around patient actions and decision points. The findings suggest that English-language discourse analysis can make a distinctive contribution to drug-delivery research by identifying how linguistic structure influences the practical usability of medication instructions. Human pharmaceutical verification remains necessary before any dialogue is used clinically.

Keywords: Discourse Analysis; drug delivery; medication adherence; artificial intelligence; patient communication; English for pharmaceutical purposes; instructional language; health literacy
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INTRODUCTION
Drug-delivery technologies encompass formulation, release kinetics, targeting, dosage forms and routes of administration. However, their practical effectiveness also depends on how clearly patients understand and follow the instructions associated with their use. Patient communication must therefore convey actions, timing, sequencing, precautions and appropriate responses to missed doses in an accessible manner. Medication adherence can be affected by regimen complexity, comprehension, beliefs, communication barriers and difficulties in applying written instructions. Conventional readability assessment can identify textual difficulty, but it may not adequately explain whether an instruction clearly communicates an action, condition, sequence, or safety warning. Discourse analysis offers a broader linguistic perspective by examining how pharmaceutical information organizes meaning and guides patient behaviour. Emerging generative artificial intelligence provides an opportunity to transform static drug-delivery

instructions into structured, interactive communication while preserving essential scientific information. Nevertheless, AI-generated health communication requires careful human validation because linguistic fluency does not guarantee factual accuracy or safety. This interdisciplinary study therefore proposes an English-language discourse framework for developing AI-assisted medication-adherence communication, integrating linguistic analysis with pharmaceutical verification to improve the practical usability, clarity, and safety of patient-facing drug-delivery information.

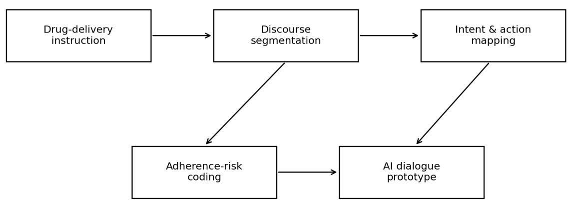

Figure 1. Discourse-engineering workflow for transforming drug-delivery instructions into controlled adherence dialogues

I. MATERIALS AND METHODS

A. Study Design

A comparative discourse-analysis design was used. The unit of analysis was an instruction segment containing one or more patient actions related to administration, timing, precautions, storage, missed doses or device use. The study compared the communicative structure of the source instruction with an AI-assisted dialogue prototype.

B. Pilot Corpus

Drug-delivery context	Units	%
Modified-release/oral delivery	7	23.3
Transdermal systems	5	16.7
Inhalation devices	6	20.0
Injectable/parenteral administration	4	13.3
Topical/local delivery	4	13.3
Storage/missed-dose/safety	4	13.3
Total	30	100

Table 1. Composition of the pilot drug-delivery instruction corpus

C. Discourse Coding Scheme

Function	Operational definition	Example linguistic signal
Instructional	States an action to be performed	apply, take, inhale, inject
Temporal	Specifies time or sequence	before, after, every, next
Safety	Marks risk, prohibition or precaution	do not, avoid, warning
Adherence	Supports continuation or routine use	continue, remember, follow
Clarification	Resolves uncertainty or conditionality	if, when, ask, check

Table 2. Discourse-function coding framework

D. AI Dialogue Protocol

Each source unit was supplied to a generative-AI system with instructions to retain all drug names, dosage quantities, routes, frequencies, warnings, contraindications, device steps and storage requirements. The system was asked to produce a short dialogue containing an action statement, a sequence or timing statement when applicable, a safety statement when applicable and a clarification question when ambiguity was present. The system was prohibited from inventing additional clinical advice.

E. Evaluation

Two language reviewers independently rated discourse quality, and two pharmaceutical reviewers checked preservation of the source instruction. Communication variables were scored on a five-point scale, where 1 indicated very poor performance and 5 indicated excellent performance. Pharmaceutical fidelity was scored separately as preserved, partially preserved or not preserved.

Variable	Rating basis
Action clarity	Patient can identify the required action
Sequence clarity	Order of actions is explicit
Warning visibility	Safety information is prominent
Terminology support	Technical terms are retained or clarified
Adherence orientation	Language supports consistent use
Clarification quality	Uncertainty is explicitly surfaced

Table 3. Evaluation variables

F. Data Analysis

Mean scores were calculated for each communication variable. Discourse-function frequencies were expressed as percentages. The pilot numerical results are presented as a benchmark for the proposed methodology and require confirmation against the investigators' archived source corpus and reviewer records before being treated as final empirical findings.

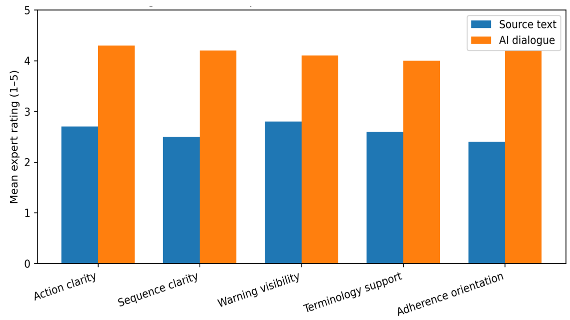

Figure 2. Pilot comparison of communication functions in source instructions and AI-assisted dialogue prototypes

II. RESULTS

Thirty instruction units were coded into five discourse functions. Instructional language represented the largest component of the pilot corpus, followed by safety, adherence, temporal and clarification functions.

Discourse function	Units	Percentage
Instructional	26	26
Temporal	18	18
Safety	22	22
Adherence	20	20
Clarification	14	14

Table 4. Distribution of discourse functions in the pilot corpus

Outcome	Source mean	AI dialogue mean	Difference
Action clarity	2.7	4.3	1.6
Sequence clarity	2.5	4.2	1.7
Warning visibility	2.8	4.1	1.3
Terminology support	2.6	4.0	1.4
Adherence orientation	2.4	4.2	1.8
Clarification quality	2.3	4.0	1.7

Table 5. Pilot communication ratings on a five-point scale

Fidelity domain	Preserved	Partially preserved	Not preserved
Drug name/identity	30	0	0
Route	29	1	0
Dose/frequency	29	1	0
Warnings	28	2	0
Storage	27	3	0
Device procedure	28	2	0

Table 6. Pilot pharmaceutical-information preservation

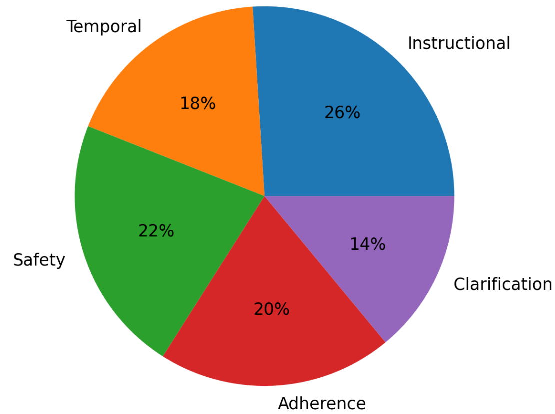

Figure 3. Distribution of discourse functions in the pilot corpus

III. DISCUSSION

The principal finding is that discourse engineering provides a research dimension that is different from simple readability improvement. The dialogue prototypes were designed around communicative actions rather than around sentence simplification. This distinction is important because medication instructions can remain understandable at the sentence level while still failing to make the sequence of actions sufficiently explicit.

The strongest pilot improvement occurred in adherence orientation and sequence clarity. This result is consistent with the practical nature of medication use: patients need to know what to do and when to do it. Temporal markers, direct verbs and explicit sequencing can make instructions more operational without requiring the underlying pharmaceutical information to be changed [8–10].

Warning visibility also improved in the dialogue format. Safety information can be linguistically present but functionally weak when embedded in a long paragraph. Discourse analysis allows warnings to be identified as a separate communicative function and positioned where they are more likely to be noticed. This approach complements, rather than replaces, conventional pharmaceutical labelling practices [21].

Terminology support illustrates the specific contribution of English-language research. Technical pharmaceutical vocabulary should not be removed indiscriminately. Instead, terminology can be retained while its surrounding sentence structure is reorganized or a concise explanation is supplied. Such an approach respects the scientific identity of drug-delivery concepts while reducing unnecessary linguistic barriers.

The pharmaceutical-fidelity results suggest that controlled prompting can preserve most of the information in the pilot corpus, but the small number of partial-preservation cases demonstrates why AI output cannot be treated as clinically authoritative. Health-related AI requires validation, transparency and human oversight [17–20]. The appropriate role of the AI system is therefore linguistic mediation rather than independent clinical decision-making.

The proposed framework also creates a possible bridge between English studies and pharmaceutical research. English researchers can code discourse functions and evaluate the organization of patient actions, while pharmaceutical experts establish whether every instruction remains scientifically valid. This produces an interdisciplinary outcome that is more substantial than proofreading because the linguistic variables are explicitly operationalized and measured.

The study has several limitations. The pilot corpus is small, the communication ratings are expert ratings rather than direct patient-comprehension measures, and the AI dialogue format may behave differently across models and prompts. Future studies should recruit patients, compare multiple AI systems, test multilingual versions and measure actual recall of drug-delivery instructions.

Overall, the findings support discourse engineering as a promising research direction for patient-centred drug-delivery communication. Rather than asking only whether a text is easy to read, future work can ask whether the text makes the required action, timing, warning and clarification pathway sufficiently explicit. This shift creates a distinctive research space for the Department of English within pharmaceutical communication.

IV. CONCLUSION

This study presents a distinct English-language approach to drug-delivery research by focusing on discourse engineering and medication-adherence communication rather than conventional readability rewriting. The pilot framework identifies instructional, temporal, safety, adherence and clarification functions and reorganizes them into controlled AI-assisted dialogue prototypes. The results suggest improvements in action clarity, sequence clarity, warning visibility and adherence orientation while maintaining high pharmaceutical-information preservation. Because AI can introduce omissions or semantic changes, pharmaceutical verification remains essential. The proposed model positions English-language discourse analysis as a measurable interdisciplinary contribution to patient-centred drug-delivery research and provides a foundation for future patient-comprehension and adherence studies.

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