Simplifying healthcare communication: Evaluating AI-driven plain language editing of informed consent forms

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Abstract

Clear communication between patients and healthcare providers is crucial, particularly in informed consent forms (ICFs), which are often written in complex, technical language. This paper explores the effectiveness of generative artificial intelligence (AI) for simplifying ICFs into Plain Language (PL), aiming to enhance patient comprehension and informed decision-making. Using a corpus of 100 cancer-related ICFs, two distinct prompt engineering strategies (Simple AI Edit and Complex AI Edit) were evaluated through readability metrics: Flesch Reading Ease, Gunning Fog Index, and SMOG Index. Statistical analyses revealed statistically significant improvements in readability for AI-simplified texts compared to original documents. Interestingly, the Simple AI Edit strategy consistently outperformed the Complex AI Edit across all metrics. These findings suggest that minimalistic prompt strategies may be optimal, democratising AI-driven text simplification in healthcare by requiring less expertise and resources. The study underscores the potential for AI to significantly improve patient-provider communication, highlighting future research directions for qualitative assessments and multilingual applications.

1 Introduction

Clear communication between patients and healthcare providers is fundamental to effective healthcare delivery (Montalt-Resurrecció et al., 2024). In this context, informed consent forms (ICFs) are an essential element of this communication, ensuring that patients are aware of the reasons for the procedures they need, as well as the risks and benefits involved (Nijhawan et al., 2013). However, ICFs are usually written in highly technical language to minimise ambiguity, which could have legal consequences (Resnik, 2009). While this precision is necessary, it often results in complex texts that are difficult for patients to understand and could raise ethical concerns about the extent to which consent is truly informed. The recent popularity of generative artificial intelligence (AI) has made advanced large language models available to the public, which can facilitate language tasks such as text simplification (Brown et al., 2020). Consequently, this research aims to explore whether AI can be used in a human-centred way to augment users (Briva-Iglesias, 2024), and more specifically, intends to analyse the potential of AI in healthcare text simplification. We seek to respond to the following research questions:

RQ1. *Can AI-generated simplifications of ICFs produce documents that are statistically significantly more comprehensible for patients?*

RQ2. *What type of prompt engineering strategy yields better readability results?*

The paper is structured as follows: Section 2 presents an overview of the literature on readability and plain language practices in healthcare contexts. Section 3 describes the methodology, detailing dataset selection, the AI system utilised, the two prompt engineering approaches tested, and the evaluation metrics applied. Section 4 analyses and presents the results obtained, comparing the effectiveness of the different prompt engineering strategies. Finally, Section 5 discusses the results and outlines implications for clinical practice, patient-provider communication, and future research directions.

2 Related work

Access to information "through any media and regardless of frontiers," as stated in the Universal Declaration of Human Rights (United Nations, 1948), is a human right linked to freedom of expression and opinion. However, differences in reading comprehension, language skills and education lev-

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els often become barriers to fulfilling this right (Halloran, 2023).

As society moves towards a more inclusive perspective, Easy and Plain Language (E/PL) have become essential in bridging the existing communication gaps. These approaches aim to remove linguistic barriers, with the objective of "mak[ing] content comprehensible and enabl[ing] the primary target groups to gather information as a basis for their decision-making" (Maaß, 2020). In doing so, E/PL empowers individuals to access, understand, and engage with information more effectively. Easy Language (EL) and Plain Language (PL) are considered to be "varieties of different national languages with reduced linguistic complexity" (Hansen-Schirra and Maaß, 2020); however, it is important to make a distinction between the two.

While both stand for increased comprehensibility, EL represents "the maximally comprehensible variety of a natural language" (Maaß, 2020). EL was initially established as a language variety for people with learning disabilities, that was later opened to other target groups (Ahrens, 2020), such as people with aphasia, dementia or hearing impairments, functional illiterates, and non-native speakers (Berget and Bugge, 2022). However, recent studies have shown that EL has the potential to stigmatise its users as it makes communication challenges or impairments apparent (Maaß, 2020).

As Hansen-Schirra and Maaß (2020) note, "the simplicity and uniformity of EL texts have a stigmatising effect on their users," whereas this effect is reduced in PL, which appears as an intermediate variety between EL and standard language. PL, often referred to as Plain English (PE) in Anglophone contexts, is defined in the United States Plain Writing Act of 2010 as "writing that is clear, concise, well-organized, and follows other best practices appropriate to the subject or field and intended audience," noting that what is considered plain to one group of readers may not be plain to others (United States General Administration, 2023).

As such, one of the main recommendations when writing in PL is to consider who is the target audience, a principle emphasised by organisations like the Irish National Adult Literacy Agency (NALA) (2024) or the U.S. General Services Administration (United States General Administration, 2023). NALA also stresses the importance of using personal, simple, and direct language, defining any technical terms and abbreviations used, keeping sentences concise (15-20 words long on average), and structuring information clearly in relatively short paragraphs. Visual presentation—such as clear formatting, spacing, and headings—should also be considered to ensure the text is not overwhelming (National Adult Literacy Agency, 2024).

Today, many governments have recognised the importance of PL on the road to equity. However, the legal and regulatory framework for its implementation is still in a developing stage. Some of the more notable efforts include the aforementioned United States Plain Writing Act of 2010, which requires federal agencies to use clear and concise language in their communications (United States Senate, 2010).

Progress was also made in Ireland with the Plain Language Bill of 2019, entitled "Act to ensure that all information for the public from government and State bodies is written and presented in plain language." However, it lapsed in January 2020 (Houses of the Oireachtas, 2019). More recently, New Zealand has enacted the Plain Language Act 2022, which aims to improve accessibility by requiring officials to communicate clearly with the public (New Zealand Government, 2022). At a global level, ISO 24495-1 on PL, published by the International Organisation for Standardisation (ISO) in June 2023, provides a global benchmark for clear communication.

Australia has played a key role in its development through the International Plain Language Federation (IPLF) (Plain Language Association International, 2025; ISO, 2023). In addition, Australia has actively promoted plain language across government and the private sector, and adopted the standard as an Australian Standard in 2024 (Plain Language Association International, 2025).

Some other countries have also adopted the new standard. Norway made it the national standard in December 2023, followed by South Africa, which adopted the standard in March 2024. Meanwhile, Canada has not officially adopted the standard, but its national guidelines are in line with the ISO principles (Plain Language Association International, 2025).

Furthermore, while the EU has not yet introduced comprehensive PL legislation, it does promote clear communication through specific regulations. This is the case of the General Data Protection Regulation (GDPR), which requires 'clear and plain language' (European Union, 2016) in all communications related to the processing of personal data; the European Accessibility Act (EAA), which aims to ensure that key products and services in the EU are designed to be accessible, including aspects of clear communication (European Union, 2019); or the EU Clinical Trials Regulation (CTR), which requires transparency in clinical trials, including easily accessible information in the EU database (European Union, 2014). These regulations underscore the growing recognition of PL's importance across various sectors, and healthcare is a crucial area of application.

The healthcare sector has long recognised and documented the challenges posed by low health literacy in the general population. As early as 2007, Stableford and Mettger (2007) identified PL as a "logical and flexible response" to these issues. Incorporating PL into patient-provider communication makes it easier for patients to find, understand, and use the information they need (Halloran, 2023), which can lead to better health outcomes, "including emotional health, symptom resolution, and functional status" (Yen et al., 2024).

As a result, healthcare professionals have increasingly advocated the use of PL in patient communication and patient education (e.g. Quesenberry (2017); Grene et al. (2017)). Some of these initiatives include the creation of PL materials and guides for specific medical contexts, such as Abrams and Dreyer (2008), who created a series of PL handouts for paediatric patients and their parents, recognising the importance of clear communication across different age groups; or van der Giessen et al. (2021), who created a PL guide for genetic counselling of breast cancer patients.

Recent advances in technology have opened the door to new methods of improving health literacy. Professionals have discussed the possibility of incorporating tools such as machine translation (e.g., Ugas et al. (2025, 2024); Lawson McLean and Yen (2024)) or AI (e.g., Ovelman et al. (2024); James (2024)) from both practical and ethical perspectives. This potential has been explored in studies applying PL principles to AI-based tools.

This is the case of the study conducted by Aide and the NHS (Wharton, 2023) to help patients understand their conditions and remind them to take their medication. Other example would be FactPICO (Joseph et al., 2024), a factuality benchmark for plain language summarisation of medical texts describing randomised controlled trials, which aims to assess the effectiveness of language models in this context.

However, while these technologies are promising, their implementation must be carefully considered to ensure accuracy and maintain the nuanced communication required in healthcare settings. A key area where this concern is particularly relevant is ICFs, which are complex texts that serve as ethical and legal documents outlining a patient's consent to receive specific treatments or procedures after being adequately informed about their healthcare decisions (Nijhawan et al., 2013).

In this context, adapting ICFs to PL will help patients understand the information necessary to make informed decisions about their healthcare. The following section outlines the methodology used to assess the effectiveness of generative AI to adapt ICFs for better accessibility.

3 Methodology

This study develops a methodology to systematically evaluate the effectiveness of generative AI systems in making ICFs more accessible for patients via PL. The framework consists of four distinct phases: (1) dataset and system selection, (2) readability metrics, (3) prompt design and PL ICF generation, and (4) output analysis. The following sections describe each phase in detail.

3.1 Dataset and system selection

One of the main aspects of this study concerns the selection of texts used as a sample for analysis. The ICFs should be representative of current patient-healthcare provider communication to ensure relevant conclusions that are applicable to real contexts. To this end, a corpus of ICFs was compiled partially following Seghiri Domínguez (2017) compilation protocol, which consists of four main steps: text search, download, conversion, and storage, with an additional cleaning stage incorporated.

The search focused on ICFs covering a variety of diseases, treatments, and medical specialities. This broad search process excluded only incomplete ICFs, such as templates providing drafting guidelines for specific cases. For this study, the corpus was limited to English-language texts, though the search process could be extended to other languages in future studies.

All the relevant documents found were manually downloaded in their original format (PDF) and then converted into UTF-8 TXT files using AntFileConverter (Anthony, 2014). This process seeks to prevent layout disruptions during text processing and to ensure compatibility with corpus management tools at a later date. Following conversion, a cleaning stage was applied to remove unwanted elements caused by layout interference. These elements were mostly composed of non-alphanumeric characters generated during the conversion process, which were eliminated to improve text quality for the analysis phase.

Each ICF was then assigned a unique identifier following a structured naming convention: a three-digit numerical identifier corresponding to the order of download, followed by 'ws' (indicating it was obtained via web search), an abbreviation of the general theme ('ICF'), the full download date (yyyymmdd), and a language indicator (e.g., 'EN' for English texts). For instance, the identifier 001wsICF20250213EN refers to the first document in the corpus, downloaded on 13 February 2025.

Once labelled, the files were systematically stored in folders and subfolders based on language and file format (PDF and TXT). In the case of TXT files, an additional distinction was made between raw texts and those cleaned for analysis. For efficient corpus management, a dedicated file logged key details for each document, such as its unique identifier, source URL, download date, conversion progress, thematic categorisation, and a column for additional notes.

The result is a monolingual corpus comprising 224 informed consent forms catalogued and structured for exploitation. For the present study, only a sample of 100 ICFs was used in the analysis phase, amounting to 193,979 tokens and 1,383 types. All texts of the sample were obtained from Cancer Research UK[1]. To ensure diversity within the domain, the sample includes five different types of cancer (Acute myeloid leukaemia, Breast cancer, Colorectal cancer, Gynaecological cancer, and Lung cancer) and related therapies and treatments. Each cancer type is represented by a set of 20 texts.

Although ICFs adhere to a standardised structural framework while being adapted to different diseases and treatments, the distribution of tokens and types within the corpus varies significantly. Even if recurrent legal and medical phrases lead to a high degree of repetition, the inclusion of diverse pathologies and procedures introduces considerable lexical variation.

The second main aspect of the development of this study concerns the selection of generative AI systems. In this regard, several approaches were evaluated, including whether to use one or multiple systems. In this instance, a single system was considered more appropriate, with the possibility of expanding the study to multiple AI models based on the findings of the analysis phase in future work.

When determining which AI system to use, various models were considered, including OpenAI, DeepSeek, Google, or Perplexity models. Finally, the OpenAI model gpt-4o-2024-11-20 was chosen for this study due to its current popularity among general AI users (Ginel and Moorkens, 2024). The model was accessed through API calls.

3.2 Readability metrics

The ICFs were evaluated using three different metrics that allow for a preliminary assessment of their readability: the Flesch Reading Ease (Flesch, 1948), the Gunning Fog Index (Gunning, 1952), and the SMOG Index (Mc Laughlin, 1969). These metrics were measured for each of the clean TXTs compiled.

The Flesch Reading Ease (FRE), based on sentence length and syllable count, is the most general of the three, as it measures the overall reading difficulty and accessibility of a text. FRE results are presented on a scale ranging from 0 to 100, where higher scores indicate easier readability. Texts that score under 50 are considered to be difficult, where 50 indicates an undergraduate reading level and 30 a postgraduate reading level.

Meanwhile, the Gunning Fog Index (GFI) serves as a broader measure of readability. It incorporates into its analysis both sentence length and the frequency of complex words, defined as words with three or more syllables. As a result, it provides insight into some aspects of structural and lexical difficulty. GFI results estimate the number of years of education required to understand a text, with scores typically ranging from 1 to 17, where 17 or higher suggests a postgraduate reading level.

In contrast, while the GFI takes into account complex words in general, the SMOG Index is specifically designed to focus on polysyllabic words, making it particularly useful for identifying complex or specialised terminology. When it comes to medical texts and, therefore, ICFs, the prevalence of technical terms can significantly affect text accessibility for patients (Dahm, 2012). The results provided by SMOG indicate the minimum school grade, based on the United States schooling system, needed to fully understand a text.

[1]Link: https://www.cancerresearchuk.org/health-professional/treatment-and-other-post-diagnosis-issues/consent-forms-for-sact-systemic-anti-cancer-therapy

Similarly to the GFI, the scale typically stops at 17, where texts that score 17 or higher require a post-graduate knowledge level. However, unlike in the previous index, the scale starts at 4.

Each of the metrics addresses specific surface-level features of readability and, when combined, they offer a preliminary analysis of textual difficulty, including sentence complexity and word length. However, it is important to note that these indices do not account for deeper aspects of language, such as discourse structure, conceptual clarity, or terminological consistency in the theoretical sense. As such, they serve as an initial tool for exploring textual accessibility, particularly in a pilot context. These readability metrics are essential to address the research questions posed by this study and were run simultaneously using a Python script that processed all texts at once and returned the scores on their respective scales.

3.3 Prompt design and PL ICF generation

Having selected the model gpt-4o-2024-11-20 as the AI system for this study, the next step was to design the prompts. This study used two distinct prompt engineering strategies to generate PL ICFs (see Table 1 in Appendix A for observing the detailed prompts). The objective was to assess which approach yielded more effective results in terms of readability and comprehensibility.

The first approach employed a simple, minimalistic prompt strategy, primarily instructing the generative AI system to simplify texts into PL without extensive additional guidance (hereafter, "Simple AI Edit"). The Simple AI Edit allowed us to evaluate the AI system's innate ability to independently produce accessible text simplifications.

The second approach involved a more detailed, structured prompt, explicitly providing comprehensive instructions aligned with officially recognised best practices in PL (hereafter, "Complex AI Edit"). The prompt of the Complex AI Edit included clear guidance on readability, text structure, and formatting, explicitly encouraging the use of short paragraphs, lists, and other elements aimed at enhancing accessibility and comprehension. Besides, the prompt included an attached document, namely the "Writing and design tips" document of the Irish National Adult Literacy Agency (2024), which provides best practices on how to write and design documents and materials so that they are easier to read, understand and use.

Both prompt strategies were systematically applied to the original TXT files through 200 API calls. The outputs were initially generated in Markdown format and subsequently converted to plain UTF-8 TXT files to remove formatting that could affect readability metric calculations. These simplified texts were then processed using the readability metrics outlined in Section 3.2.

Following best practices in transparency and reproducibility, the complete dataset (including original and simplified texts) and the Python script to run the readability metrics and visualise the graphs are publicly available for replication, open research and further analysis at the following Zenodo link.

3.4 Statistical analyses

To assess whether AI-based PL editing statistically significantly altered the readability of the ICFs, paired sample t-tests were conducted. Given that the same set of documents was analysed under three different configurations (Original, Simple AI Edit, and Complex AI Edit), this statistical test was deemed appropriate to account for within-subject differences. For each of the metrics in Section 3.2, paired-sample t-tests were conducted to compare the following conditions: (i) Original vs. Simple AI Edit; (ii) Original vs. Complex AI Edit; (iii) Simple AI Edit vs. Complex AI Edit. A significance threshold of 0.05 was applied.

4 Results

The analyses conducted on the readability of ICFs reveal significant differences across the three document conditions assessed: Original, Simple AI Edit, and Complex AI Edit. Figure 1 demonstrates that, overall, the documents simplified through the Simple AI Edit approach yielded the best readability metrics. Documents generated using the Complex AI Edit strategy followed, while the original, unedited documents consistently showed the worst readability scores.

4.1 SMOG Readability Score

A series of paired-sample t-tests were conducted to determine whether AI-based PL editing significantly affected SMOG scores. A statistically significant reduction in SMOG scores ($t(99) = 52.17$, $p < .001$) was observed when comparing the Original version ($M = 13.88$; $SD = 0.34$) and the Simple AI Edit version ($M = 11.26$; $SD = 0.46$), indicating that the Simple AI Edit significantly simplified the texts.

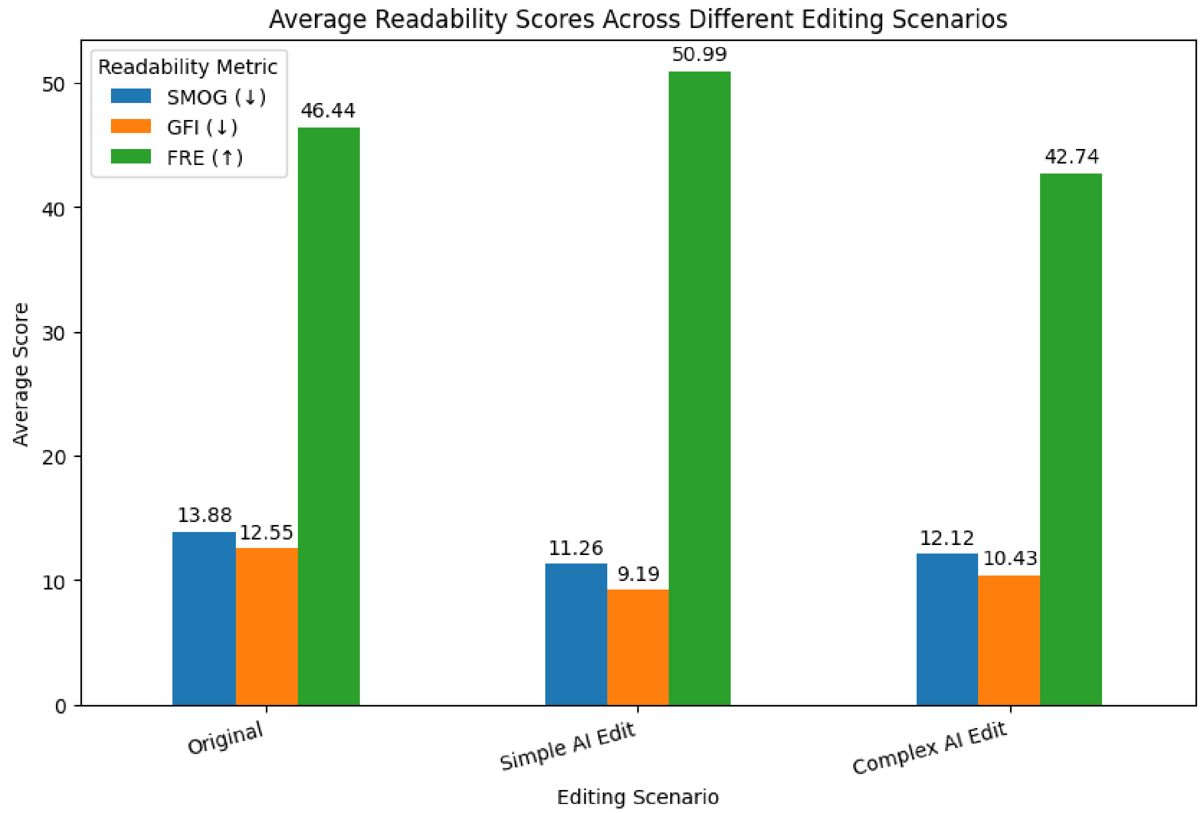

Figure 1: Readability Results.

SMOG scores were also statistically significantly lower (t(99) = 29.77, p < .001) in the Complex AI Edit (M = 12.12; SD = 0.48) compared to the Original version. Furthermore, the difference between the Simple AI Edit and Complex AI Edit was also statistically significant (t(99) = -14.35, p < .001), indicating that the Simple AI Edit resulted in greater simplification.

4.2 Gunning Fog Index (GFI)

Similar analyses were performed for the GFI metric. When comparing Original documents (M = 12.55; SD = 0.52) to the Simple AI Edit documents (M = 9.19; SD = 0.48), a statistically significant decrease in GFI scores was found (t(99) = 48.76, p < .001), confirming substantial text simplification by the Simple AI Edit.

Likewise, the Complex AI Edit documents (M = 10.43; SD = 0.67) showed a significant reduction in GFI scores compared to the Original documents (t(99) = 22.57, p < .001). Again, the difference between the two AI editing strategies was statistically significant (t(99) = -15.66, p < .001), reinforcing the greater effectiveness of the simpler prompt in reducing text complexity.

4.3 Flesch Reading Ease (FRE)

Regarding FRE scores, the comparison between Original documents (M = 46.44; SD = 4.22) and Simple AI Edit documents (M = 50.99; SD = 4.14) revealed a significant increase in readability scores (t(99) = -8.40, p < .001), indicating improved readability in the AI-edited documents. Interestingly, when comparing the Original vs Complex AI Edit documents (M = 42.74; SD = 4.04), results share a different story. In this comparison, the statistically significant difference (t(99) = 6.65, p < .001) indicates that the Original documents have higher readability than the documents generated via the Complex AI Edit.

Finally, when directly comparing Simple AI Edit and Complex AI Edit, the Simple AI Edit documents also demonstrated statistically significantly higher readability improvements (t(99) = 14.68, p < .001), underscoring the superior effectiveness of the simpler prompt strategy.

5 Discussion of the results

The findings of this study highlight the considerable potential of AI to significantly enhance the readability and comprehensibility of ICFs, essential documents within patient-provider communication (Nijhawan et al., 2013). Overall, the Simple AI Edit prompt consistently demonstrated superior effectiveness in simplifying text compared to both the Complex AI Edit and the original documents, suggesting that minimalistic yet clear instructions to generative AI systems might yield optimal results in this specific use case (see Table 2 in Appendix A for consulting a brief excerpt from the results).

Interestingly, this finding democratises the use of AI-driven PL editing, as the effort and expertise required to achieve excellent readability results are significantly reduced. Thus, healthcare providers and institutions with limited resources or technical expertise can easily integrate AI-driven simplification strategies to improve patient-healthcare provider communication.

The statistically significant reductions observed across SMOG and GFI scores clearly indicate that AI can effectively reduce text complexity, particularly through simplifying medical terminology and sentence structures. This improvement is critical in healthcare contexts where patient comprehension directly influences the quality of consent and decision-making. The Simple AI Edit strategy, with its straightforward prompt, consistently produced greater readability improvements than the more detailed and structured Complex AI Edit, which incorporated extensive PL guidelines. This result underscores the importance of simplicity and directness when guiding generative AI systems in readability enhancement tasks.

Another interesting result was that AI Plain Language editing consistently outperformed original documents across all readability metrics, except in the case of the FRE score when comparing Original documents with Complex AI Edit documents. This deviation suggests that overly detailed prompt instructions may inadvertently limit the AI system's natural simplification abilities, potentially resulting in outputs that remain closer to the original texts in terms of readability. This is supported by previous research on the importance of appropriate prompt engineering in every specific use case (Sahoo et al., 2024). Consequently, future prompt designs might benefit from balancing specificity with flexibility to optimise AI-generated readability improvements.

6 Conclusion

This study demonstrated the significant potential of AI for enhancing the readability and comprehensibility of ICFs. The findings revealed that simpler prompt instructions (Simple AI Edit) consistently achieved better readability outcomes than more complex prompts (Complex AI Edit), highlighting the feasibility and efficiency of minimalistic prompt strategies in healthcare communication contexts.

Despite these promising results, certain limitations should be acknowledged. Primarily, this research was conducted exclusively in English, thereby restricting the generalisability of the conclusions to other languages, particularly minor languages that may have different linguistic and structural complexities and less training data for AI systems, resulting in lower quality AI output (Briva-Iglesias, 2022; Briva-Iglesias et al., 2024).

Additionally, the analysis conducted was strictly quantitative, leaving qualitative aspects unexplored—specifically, whether the AI-driven simplifications inadvertently suppress crucial medical or legal information necessary for informed patient decision-making. Future research should therefore incorporate qualitative evaluations to comprehensively assess the content integrity and accuracy of AI-generated simplified documents. Such analyses will ensure that readability improvements do not compromise critical informational elements essential for informed consent.

Expanding this research to other languages and healthcare domains beyond informed consent forms could also provide further insights into the broader applicability and effectiveness of generative AI in terms of PL simplification strategies, ultimately contributing to improved patient-healthcare provider communication across diverse linguistic and medical contexts.

Furthermore, future studies should explore the impact of model size on the effectiveness of AI-driven simplification strategies. The present research utilised a large language model; however, investigating smaller models is crucial, given the importance of token usage, computational resource consumption, and sustainability considerations (Moorkens et al., 2024). Analysing the trade-off between output quality and resource efficiency could provide valuable insights into optimising generative AI applications in healthcare communications.

The implications of these results extend into clinical practice, suggesting that healthcare providers and administrators could efficiently implement simple AI-based text editing methods to produce clearer, more comprehensible documents. This could significantly enhance patient autonomy and participation in healthcare decisions, fostering more ethical and effective patient care. Additionally, this research contributes valuable insights to the broader fields of health literacy and patient-provider communication by illustrating practical strategies to bridge the persistent gap between medical precision and patient comprehension.

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A Appendix

This Appendix contains Table 1 (the prompts used for both the Simple AI Edit and the Complex AI Edit) and Table 2 (a small excerpt from one of the ICFs analysed with the results with the original and both AI edits).

Condition	Prompt
Simple AI Edit	Transform the following document into Plain Language so that it is more understandable. Do not suppress or remove any of the information.
Complex AI Edit	Transform the following document into Plain Language by considering the enclosed document and the following recommendations. Do not suppress or remove any of the information. **Writing Style** *Know Your Audience* Consider who will read your text and what they already know. Use familiar words and concepts. Keep the tone and detail level appropriate for your audience. *Use Clear and Direct Language* Prefer "we" (for your organisation) and "you" (for the reader). Make it clear who is responsible for actions (e.g., "We will contact you" instead of "You will be contacted"). *Choose Simple Words* Avoid jargon, corporate language, and complex words. If a simpler word conveys the same meaning, use it (e.g., "use" instead of "utilise"). *Explain Technical Terms and Abbreviations* If a technical term is necessary, define it the first time. Spell out abbreviations when first mentioned and limit their use. *Keep Sentences Concise* Aim for 15–20 words per sentence. Express one idea per sentence. Avoid unnecessary phrases. **Structure** *Prioritise Reader's Needs* Present information in a logical order. Start with the most important points. *Use Visual Formatting to Guide Readers* Include bullet points and subheadings to break up text. Leave white space to make content more readable. *Keep Paragraphs Short* Each paragraph should focus on one idea. Avoid long blocks of text.

Table 1: Prompts for the AI plain language transformation

Condition	Resulting text
Original	Common chemotherapy side effects. Affecting more than 10 in every 100 (>10%) people - An increased risk of getting an infection from a drop in white blood cells – it is harder to fight infections and you can become very ill. - If you have a severe infection this can be life- threatening. Contact your doctor or hospital straight away if: - your temperature goes over 37.5°C or over 38°C, depending on the advice given by your chemotherapy team - you suddenly feel unwell (even with a normal temperature) - Thinning of the hair or sometimes complete hair loss, watery/sore eyes, sore mouth/ulcers, feeling sick (nausea) and being sick (vomiting), tummy (abdominal) pain. diarrhoea, tiredness and feeling weak (fatigue). - Low blood pressure during treatment, fluid build- up in legs and ankles with weight gain, change in skin colour, mild allergic reactions (rash, flushing).
Simple AI Edit	Common Side Effects (happens in more than 10 out of 100 people) - Infections: A weakened immune system makes infections harder to fight. Severe infections can be life-threatening. Call a doctor if: - Your temperature is above 37.5°C or 38°C (as advised by your medical team). - You feel suddenly unwell, even with a normal temperature. - Thinning or loss of hair. - Watery or sore eyes. - Sore mouth and ulcers. - Nausea and vomiting. - Abdominal (tummy) pain. - Diarrhoea. - Tiredness and weakness (fatigue). - Low blood pressure during treatment. - Fluid build-up in the legs and ankles, leading to weight gain. - Skin color changes, mild allergic reactions (rash, flushing).
Complex AI Edit	Common Side Effects (More than 10% of patients may experience these) - Increased risk of infections due to low white blood cells. Severe infections can be life-threatening. - Seek medical help if your temperature is over 37.5°C or 38°C (based on chemotherapy team advice). - Contact your doctor if you suddenly feel unwell, even with a normal temperature. - Thinning of hair or complete hair loss. - Nausea, vomiting, diarrhoea, abdominal pain. - Sore mouth and ulcers. - Fatigue, weakness. - Muscle and joint aches and pain (which may be severe). - Numbness or tingling in hands and feet (temporary or permanent). - Fluid build-up in ankles and legs with weight gain. - Low blood pressure during treatment.

Table 2: Small excerpt from one ICF after the plain language transformation