Examining the time-and effort-saving utility of tailored AI-tooling for abstract Plain Language Summary Development

Walter Bender[a,*] | Tom Grant[b] | Veronica Porkess[b] | Margarita Lens[b] | Chris Rapier[b] | David McMinn[a]

[a]Sorcero, Washington DC, USA | [b]UCB Pharma, Slough, UK [*]Presenting author

Poster 10

Key Takeaway

Bespoke-AI technology saves medical writers time and effort when developing PLS abstracts, and helps them to reach a broader audience without any degradation of accuracy.

Background

- Several studies have shown that plain language summaries (PLS) of scientific content are not fit for purpose. Analysis indicates that they are difficult to read for a lay population without medical education, greatly limiting their accessibility.[1-4]
- To address this shortcoming, we tested a bespoke generative-AI (BAI) process to assess its efficacy at generating PLS abstracts for a lay population.

Objectives

- The primary aim of the study was to assess time and effort savings of using a BAI process for PLS abstract development by professional medical writers (PMWs).
- Secondary aims were to assess the quality of the output by subject-matter experts (SMEs), the suitability of the results as a vehicle for discussion with their patients by primary-care physicians (PCPs), and the reading level of the output.

Methods

PMW Tasks

- PMWs (n=10; 4 US, 5 UK, 1 FR) were each given 6 scientific abstracts and asked to write corresponding first-draft PLS abstracts. The therapeutic areas of the six articles were rare neurological and rheumatological diseases. One article was concerned with a Phase 2 trial; four articles were concerned with Phase 3 trials; one article was a survey-based study.
- In task condition 1, the PMWs were asked to write PLS abstracts from scratch, based on two original scientific (OS) abstracts, randomly selected. They were instructed to forgo using any AI tools while completing this task.
- In task conditions 2 and 3, the PMWs were asked to manually review/edit/revise four randomly selected AI-generated PLS abstracts as necessary to develop first drafts.
  - » In condition 2, one of the four AI PLS abstracts had been generated using a non-bespoke AI (NBAI) process via a publicly-available interface.
  - » In condition 3, the other three AI PLS abstracts were generated using a proprietary multi-stage BAI process that employs several large language models and task-specific coding (tooling).
- PMWs were given the corresponding OS abstract as a reference in all three task conditions.
- The PMWs scored each PLS abstract for task completion time (minutes) and task effort (0-9 scale; higher scores reflect more effort required).[5] The task condition order and the abstract types were assigned randomly to control for any potential learning or ordering bias. PMWs were blind to the abstract type *(See Figure 1)*.

SME Tasks

SMEs (n=3) assessed the PLS abstracts from both tasks (n=72, randomly assigned across the SME pool) for accuracy on a Likert rating scale (1-5; higher scores reflect better accuracy). SME reviewers were blinded to the abstract type.

PCP Tasks

The PCPs (n=7; 3 US, 4 EU) assessed the PLS abstracts from both tasks (n=72, randomly assigned across the PCP pool) for clarity on a Likert rating scale (1-5; higher scores reflect better clarity). PCP reviewers were blinded to the abstract type.

Additional Measurements:

- The readability of the OS, PMW, NBAI, and BAI PLS abstracts were all measured using Flesch-Kincaid Reading Level.[6] A measure of population accessibility was calculated based on the OECD PIAAC data for the United States.[7]
- The Levenshtein distance[8] (the minimum number of single-character edits [insertions, deletions or substitutions]) required to change between the source and output PLS abstract was also calculated.
- SMEs and PCPs reported whether they thought each PLS abstract was developed by a human or by generative AI.

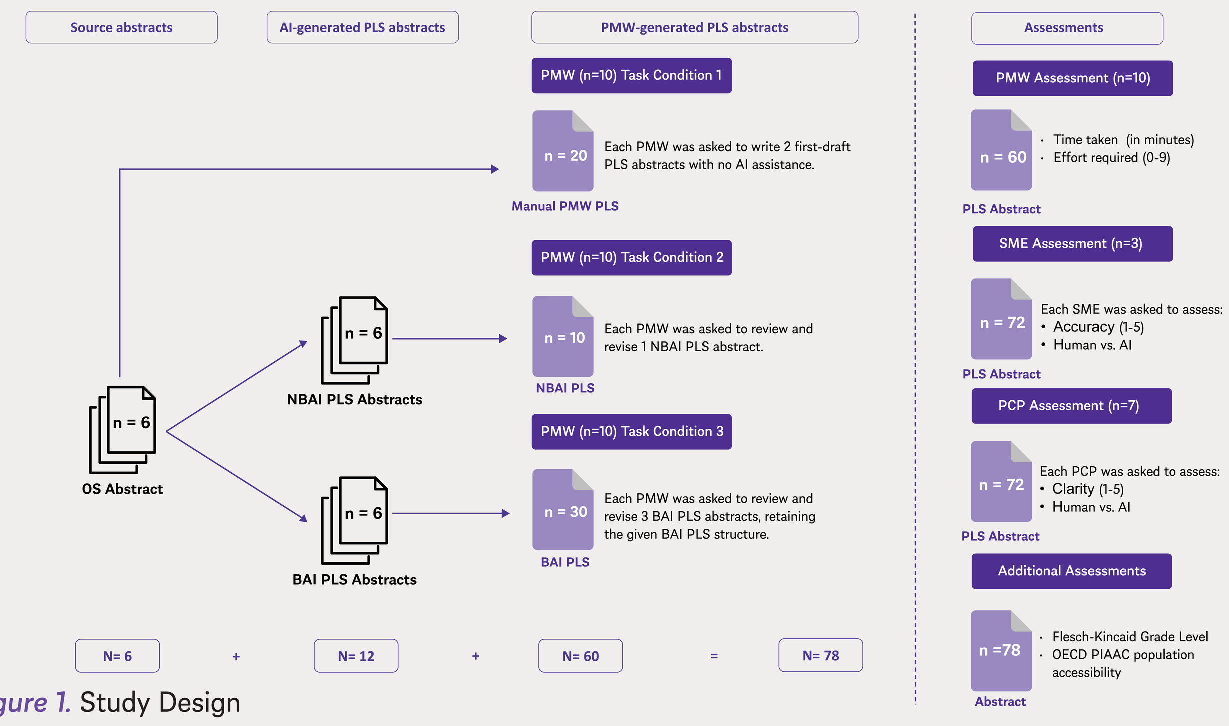

Figure 1. Study Design

Results

Time and Effort

- Time to complete unassisted (manual), NBAI-assisted, and BAI-assisted PLS abstracts are shown in *(Figure 2)*; there was a 41% reduction in time for BAI versus the manual process (p<0.001).
- Effort to complete unassisted (manual), NBAI-assisted, and BAI-assisted PLS abstracts is shown in *(Figure 3)*; both manual and NBAI processes required relatively (20%, 16%) more effort than the BAI process.

SME and PCP assessments

- SME accuracy assessments were similar for BAI-assisted and NBAI-assisted PLS abstracts, which were relatively higher than unassisted (manual) PLS abstracts *(Figure 4)*.
- SMEs correctly identified the correct development process (human vs AI) 56% of the time.
- NBAI and BAI assistance had a positive impact on the PCP end-user clarity assessments *(Figure 5)*.
- PCPs correctly identified the correct development process (human vs AI) 61% of the time.

Readability and Accessibility

- AI-assisted PLS abstracts are easier to read than PLS abstracts written manually by medical writers *(Figure 6)*.
- AI-assisted PLS abstracts are accessible (understandable) to a larger percentage of the population than either the OS abstract or the PLS abstracts written manually by medical writers *(Figure 7)*.

Levenshtein distance

- The mean Levenshtein distance between the BAI PLS abstract and the completed PMW first draft (1570) was less than that of the NBAI PLS abstract and the completed PMW first draft (1780), meaning that the writer had fewer changes to make using the BAI process vs. the NBAI process.

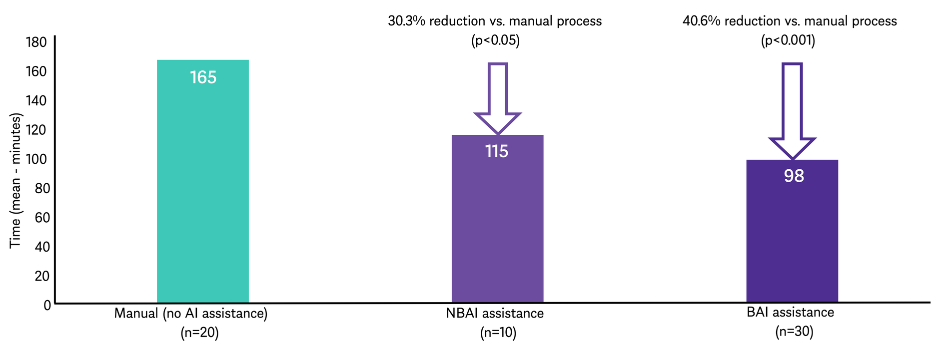

Figure 2. BAI assistance significantly reduced the time to PLS abstract completion (by 41% vs. the traditional manual method).

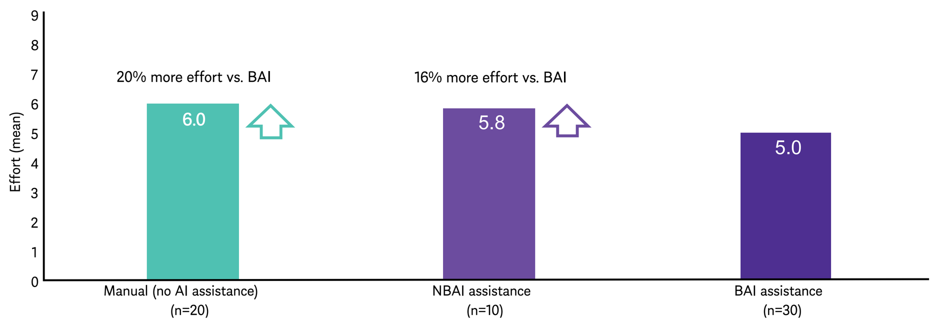

Figure 3. Both the traditional manual method and NBAI approaches required relatively (20%, 16%) more perceived effort vs. the BAI approach.

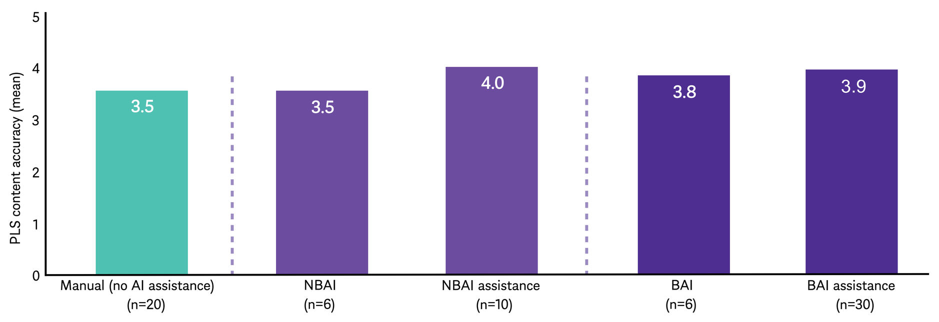

Figure 4. AI-generated PLS abstracts more accurately reflected the OS abstract than did the manual human-written PLS abstracts according to SME assessments.

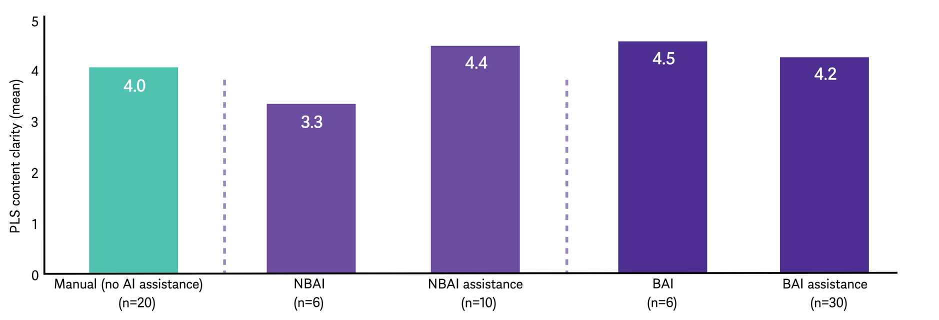

Figure 5. The BAI PLS abstract development process (before human involvement) resulted in PLS abstracts that were most suited to explaining the research findings to lay audiences according to PCP assessments.

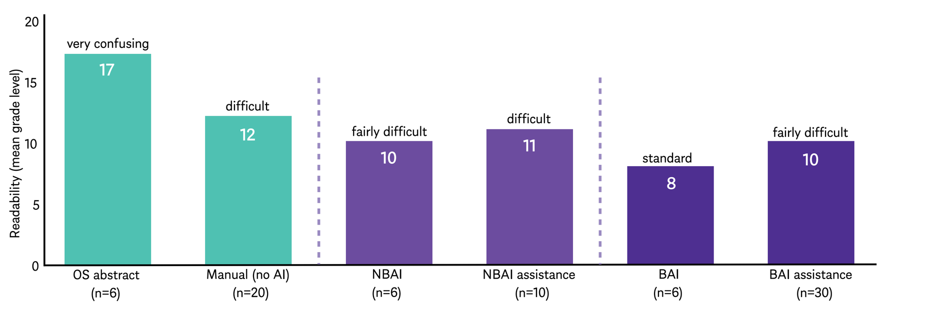

Figure 6. AI-assisted PLS abstracts are easier to read than PLS abstracts written manually by medical writers. Unrevised PLS abstracts generated using the BAI process were easiest to read.

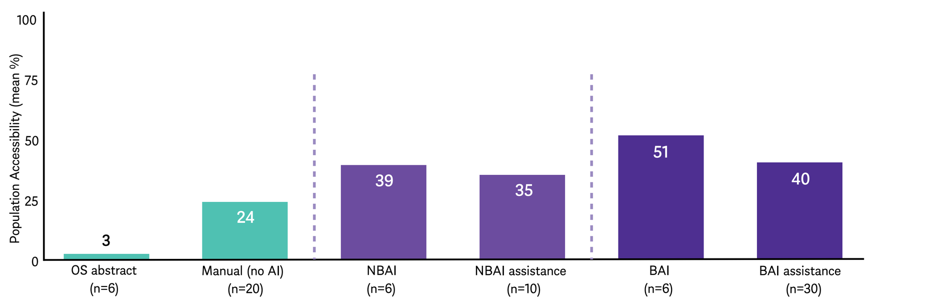

Figure 7. AI-assisted PLS abstracts are understandable to a larger percentage of the population than the original scientific abstract and the PLS abstracts written manually by medical writers.

Limitations

- Small sample size for NBAI (condition 2);
- No target grade level provided to medical writers;
- Readability metrics may not be the most suitable outcome.

Conclusions

Medical PLS abstract writing augmented with bespoke AI tooling saves significant time, and effort, without degradation of accuracy or clarity, over both human-alone or standard non-bespoke AI-assisted PLS abstract generation.

References

1. Stoll M, Kerwer M, Lieb K, Chasiotis A. PLoS One. 2022;17(6).
2. Banić A, Fidahić M, Šuto J, et al. BMC Med Res Methodol 2022;22 240.
3. Shiely F, Daly A. J Clin Epidemiol. 2023;156:105-112.
4. Ferrara T and Conran E. Porterhouse Medical Group, Reading, Berkshire, UK https://www.porterhousemedical.com/wp-content/uploads/2021/02/ISMPP-EU-2021-poster_v1.0.pdf
5. Ouwenhand K, et al. Frontiers Education 2021;6:702616.
6. Readability Formulas. Readability Scoring System (v2.0). Accessed January 8, 2024. Available at https://readabilityformulas.com/readability-scoring-system.php#formulaResults.
7. OECD Programme for the International Assessment of Adult Competencies (PIAAC) https://www.oecd.org/skills/piaac/ Date accessed: 2024-03-14.
8. Navarro G. ACM Computing Surveys 2001;33:31–88.

Acknowledgements

This study was jointly funded by UCB Pharma and Sorcero, Inc.

Disclosures

WB is an employee of Sorcero with ownership interest; DM is an employee of Sorcero; TG, VP, ML, and CR are employees and shareholders of UCB.

Abbreviations

AI, artificial intelligence; BAI PLS: Bespoke-AI plain language summary; NBAI PLS: Non-bespoke-AI plain language summary; OECD: Organisation for Economic Co-operation and Development; OS abstract: original Scientific ; PCP: primary-care physician; PIAAC: Programme for the International Assessment of Adult Competencies; PMW: professional medical writer; PMW PLS: professional medical writer plain language summary; SME: subject-matter expert.

ISMPP International Society for Medical Publication Professionals 20TH ANNUAL MEETING Storytelling: Its Art And Power

Poster presented at the 20th Annual Meeting of the International Society for Medical Publication Professionals™ (ISMPP); April 29-May 1, 2024; Washington, DC, USA

sorcero.com | info@sorcero.com