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Machine Learning Tools in the Technical Writing Classroom: A Modular Approach

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As new Machine Learning (ML) tools come online, technical writing instruction is poised to create new applied projects, teaching students to use ML constructively, objectively evaluate ML output, and refine final products faster. STEM researchers are already publishing their use of Chat GPT-adjacent language tools in high impact scientific outlets like *Nature*. Engineering students need exposure and to develop competency in using these tools. ML can support technical writing by proofreading content; suggesting novel syntactic structures; producing usable content faster; and upskilling writers in the process. This paper presents the use of four ML tools, applied in service to a series of technical writing and communication projects appropriate for sophomore-junior level students. Projects can be used in embedded technical communication modules and are scaled up for independent courses.

Changing the technical writing and communication (TWC) curriculum will prepare students to employ technical writing tools already on the market. TWC courses are typically taught in sophomore and junior year, and their curricular placement supports more technical lab-based courses and senior design courses. By employing the modular approach that this paper advocates, ML-informed technical writing projects can be scaffolded throughout the curriculum, paired with a more technical course, or tailored to a graduate seminar.

Current technical writing courses for engineers support the curriculum by improving Engineering Students' (ES) communication skills; teaching ES technical conventions; and building capacity for project management and project documentation. Engineering students become more accurate in their evaluations of Technical Writing (TW), and better able to distinguish effective and ineffective TW after working with these tools. Lastly, teaching students to use ML writing tools allow engineering educators to effectively promote these learning outcomes in novel ways, while supporting professional preparation.

1. Background

Many higher education institutions are penalizing or restricting students' use of Artificial Intelligence (AI) tools at the same time that professors and STEM practitioners are leveraging them in practical ways. As higher education seeks to identify, control, and in some cases eliminate students' use of AI or Large Language Models (LLMs), medical scholars declared ChatGPT co-authorship in over 1,000 papers on PubMed in August of 2023 [1]. Meanwhile, reviews of 'highly productive authors' since 2016 found an uptick in publication activity in Saudi Arabia and Thailand equivalent to about forty authors publishing a paper every five days, including weekends [2]. Abnormal productivity sparked an internal investigation in Thailand. It is thought that the 'publish or perish' mentality coupled with funding streams that bias toward large, interdisciplinary teams create ideal conditions for unstated recruitment of AI-assisted publication tools. Scientists are fearful of unregulated AI-generated knowledge and excited about its potential for productivity.

Who's doing AI-assisted scientific writing?

In a *Nature* survey of 1,600 scientists, two-thirds admitted to using AI language tools to summarize data and save time, with over a third of them leveraging AI to brainstorm new hypotheses, and make new discoveries. These same scientists are aware of the growing weakness in their use of AI to make sense of data—over 70% acknowledge that AI use for data-processing leads to "more reliance on pattern recognition without understanding." [3-4]. Of note, while NSF allows the incorporation of LLM-generated text, NIH does not allow the use of LLMs to produce grant proposals. Neither federal funding agency allows reviewers to use LLMs or AI-assisted tools in their reviews. Meanwhile, certain funding streams within the Department of Defense allow for LLMs to be used in document preparation.

Why are Large Language Models (LLMs) problematic?

Semantic ontologists have noted that LLMs (GPT-3) have documented weaknesses that give rise to false conclusions, false references, and algorithms that produce biased and racist processes [5-6]. LLMs are giant statistical arrays, and prompts essentially elicit a statistically likely pattern of language based on whatever content (text) is present in the training data set. As a result, misleading findings, false citations, and irrelevant content can easily be introduced into an LLM-sourced text [7]. Scientists have begun lobbying for (1) enforceable, honest use of AI; (2) an arms race in detecting AI-generated text; (3) boundaries around AI use, with some calling for an international regulation [7-9].

Everybody's Doing It

While scholars argue about what 'authorship' even means in the age of LLMS [10], what is clear is that STEM practitioners have been early adopters of this technology. Healthcare and medical scientists warn that LLM-driven AI is an "experimental technology that is not ready for prime time," [11-12] in the sense that it can only augment human decision making if it iterates within "an ethical, technical, and cultural framework for responsible design, development, and deployment."

LLMs and Engineering Education

Selected educators are advocating for the use of transparent LLM-assisted report writing, finding mixed results and some benefits for mechanical engineering and management students [13]. A major drawback to the use of LLMs in the classroom is that students have not been prepared to design 'good' AI prompts [14]. While a survey of 2023 incoming freshman showed that over half of them had used AI in some capacity for homework, students' clumsy deployment of prompts is at best luck and at-worst partly the reason the resulting text is so flawed. No one has formally taught students 'good use of AI' and in many cases students' schools have forbidden its use [15]. As Zamfirescu argues, competent use of LLMs in an engineering learning environment includes teaching students 'end-user prompt engineering' [14].

There are other examples of efforts to support students in technical writing using AI-based technologies. One instance is the Thesis Writer, developed at the Zurich University of Applied Sciences in Switzerland [16]. Unfortunately, AI technologies like Thesis Writer are generally proficient to review texts for grammar or syntax errors and are not used to check other characteristics of writing and communication (e.g. argumentation structures, relevance, coherence, etc.). They rarely redirect the writer to work on writing strategies or other supportive development. Context relevant writing and semantics are important when it comes to creating high quality technical writing. Currently, AI tools do not provide that level of writing support [17].

More recent AI tools collect data on interactions and distinguishing patterns, learn from these, and then attempt to exchange this information to users. In order to have more authentic communication with users, AI tools are now looking for conversational schemes to derive importance and meaning from user intent and emotional state during the exchange and to couple this with a meaningful response [18]. AI tools can help but need a human's (disciplinary expert) input; insufficient or imperfect inputs would lead to inadequate results. Simply stated, AI should not replace human expertise, prudence, character, and most significantly, responsibility [19].

2. Modules

The following modules were embedded in a post-baccalaureate technical writing and communication course offered to industry. Students were adult professionals working project management and engineering roles. Their supervisor requested an overview of available LLM-assisted writing tools. The following modules were integrated into the course and preceded by a cautionary note regarding proprietary ideas and data and the danger potentially present when using cloud-based platforms to process text or data. Modules 1-3 and their corresponding applications were presented, and then applied to an authentic proposal-writing opportunity. Students broke into groups to accomplish the applied task and returned to the larger group to report on results, findings, and initial impressions of using these writing tools.

Module 1: LLM-assisted Drafting (Safely): Available in free and proprietary versions, WordTune [20] is an LLM-driven drafting tool that can help engineering writers summarize, reword, and restructure sentences and paragraphs. This option is more robust than Grammarly's LLM, but requires initial input in order to provide multiple options. WordTune-revised text can be 'tuned' for conciseness, formality, level of detail, and sentence structure. Because WordTune allows for multiple sentence structure feature options, it is an ideal 'trainer' for early career engineering writers, allowing them to experiment with sentence structures they would not normally use. While its appropriateness as a pedagogical tool is clear, WordTune is one of the most highly rated writing applications for working technical writers, attesting to its modern relevance. In the following WordTune example, a published journal article in medical research is processed to yield more concise, readable text. This article was chosen because it was published before LLM-based applications existed [21].

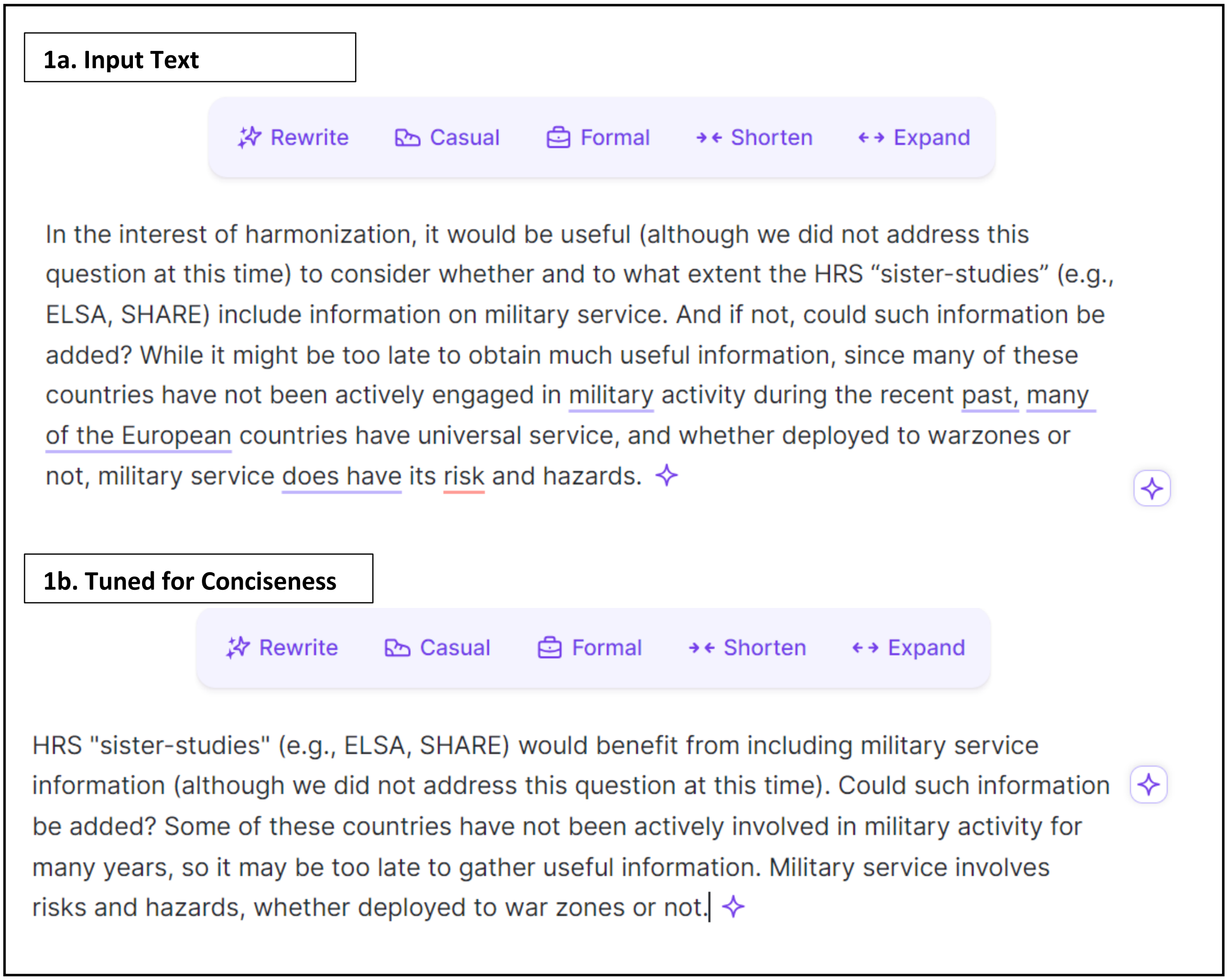

Figure 1: WordTune Text Results, Tuned for Conciseness.

Module 2: LLM-assisted Summaries for Comprehension – Explainpaper, Copyai

Sometimes, early career engineering writers are blocked by fear of the blank page, fear of failing, and general anxiety around writing. It can be helpful to jumpstart the process. Copyai [22] is a tool that essentially trains users in high quality prompt engineering, adopting a visual graphic user interface that narrows the writer's needs down by interest area. For example, in Figure 2 below, the kind, or 'genre' of text is selected first, followed by winnowing list of options to provide inspiration. By down-selecting features from a broad writing category, writers are encouraged to build a better prompt—resulting in text that can inspire and connect them with the content that truly matters to them. Arguably, this process is more interactive and takes less time than the traditional approach to generating copy, which is the freewriting technique taught in many freshman writing classes.

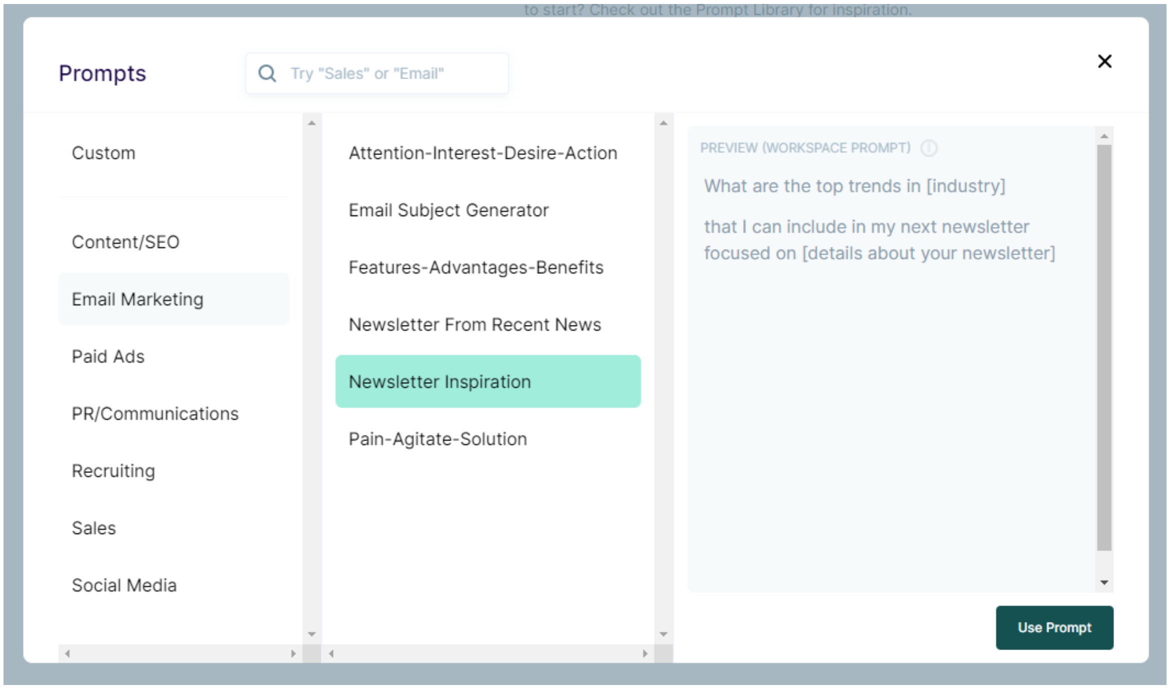

Figure 2: Copyai and Prompt Engineering.

Module 3: Detecting AI-text

AI-assisted technical writing can be transparent and ethical. AI-authorship is now allowed by NSF and NIH, and its use will become more apparent. AI-coauthored papers may be subject to higher standards of review and scrutiny, however, due to the propensity for false or misleading information to appear in LLMs. Given that higher bar, some may be tempted to not provide attribution to AI-assisted technical writing. LLM watermarking, a process whereby resulting syntactic patterns in AI-generated text mathematically 'signal' an AI source (as opposed to a human source) have been embedded in GPT-4 and other LLMs. These so-called watermarks allow for 'detectors' to provide the statistical likelihood of AI use. Some examples sourced from industry, academia, and students follow:

1) **GPT-2 Output Detector** [23]: (From Open AI, the makers of ChatGPT) Claims a detection rate of 95% for machine-generated text using GPT-2. OpenAI recommends using in conjunction with additional approaches. (95% accuracy)

2) **Giant Language Model Text Room (GLTR)** [24]: (From Harvard and IBM) (Strobelt & Gehrmann, 2019) Detects likelihood that words were predicted by a bot. Color-coded results aid interpretation.

3) **GPTZeroX** [25]: Created by Princeton University student Edward Tian for educators. Supports large text inputs and file uploading, claims to identify portions written by AI. Scores on "perplexity" and "burstiness, where perplexity is a measure of randomness and

likelihood the next word was bot-generated, and burstiness refers to variations in sentential length and complexity, as these are known features of human writing.

4) **AI Classifier** [26]: (From Open AI, the makers of ChatGPT) Indicates likelihood that text is automated or human written. Reliability increases improves with longer text, but is not guaranteed and should not be used as the only detection tool.

3. Transparent Integration of LLMs into TWC Pedagogy

Scientists, engineers, and educators are leveraging AI-assisted solutions to improve workflow, idea generation, and automate repetitive tasks. LLMs have the potential to be constructive for TWC pedagogy. When scaffolded into appropriate projects, LLMs can (1) assist in developing students' prompt engineering acumen; (2) connect novel ideas, help generate research hypotheses, and suggest analytical approaches; (3) improve input text along several dimensions—formality, level of detail, conciseness, sentence structure; and (4) serve as a tool to educate engineering students' on the true distinctions between human writing and LLM-sourced text, challenging them to find LLM-written content online (e.g., social media posts and LinkedIn blogs). Using additional tools that analyze syntax (Expresso), students can become aware of their own writing style, how it contrasts with their peers, and how to objectively alter and improve writing tendencies that challenge readability. Below in Figure 3, modules 1-3 are presented as a series of steps with the inclusion of experimentation and play, which are integral for true learning. Adult learners reported adapting and adopting selected LLM-assisted sentence structures and word-choice after repetitive exposure. Adaptation is a kind of learning and may signal that students took risks with their technical writing precisely because they believed the LLMs would produce better possibilities than their own writing, un-assisted. LLM-assisted writing does not have to limit creativity—while learners lean on LLMs early in the process, they can adapt the newly discovered writing approaches in novel domains after the fact.

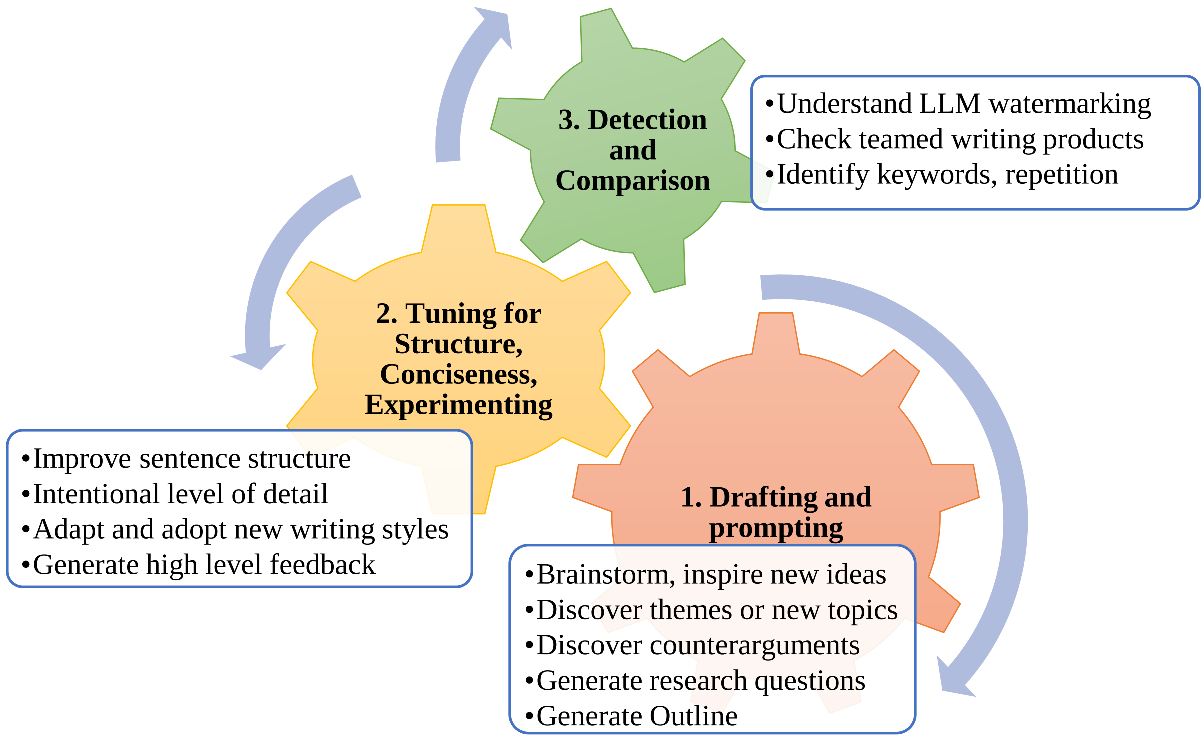

Figure 3: Staged Uses for LLMs during the Technical Writing Process.

4. Conclusion and Future Work

The focus of this work is to improve the technical writing competency of engineering students with the help of technology and to moderate the workload of instructors in technical writing. The industry students who participated in these modules were very interested in ways to safely leverage AI tools for technical and scientific writing. As this area is still evolving, contractors' rules for allowable AI-assistance is determined by the buyer or bidder. Industry continues to be further ahead than higher education in adopting these tools. Following industry's lead, this work proposes a way to incorporate AI into an academic environment where AI is seen as an ethical and transparent tool and not an absolute distractor.

AI is simply a tool that can assist human writers but should not be used as a replacement for human expertise, judgment, and personality. In the field of technical writing where content may be more important than style, AI tools should always be used in conjunction with human expertise and judgement. The engineers' work transcends more than calculations and results, and engineers often find themselves engaged in technical writing to communicate these outputs. These results may have large societal impacts, and the production of technical writing requires the oversight and guidance of human writers who are experts in the technical disciplines to ensure accuracy, logic, and credibility of the subject matter before wider dissemination and implementation.

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