Audience Impressions of Narrative Structures and Personal Language Style in Science Communication on Social Media

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Science communication increases public interest in science by educating, engaging, and encouraging everyday people to participate in the sciences. But traditional science communication is often too formal and inaccessible for general audiences. However, there is a growing trend on social media to make it more approachable using three techniques: relatable examples to make explanations concrete, step-by-step walkthroughs to improve understanding, and personal language to drive engagement. These techniques are flashy and often garner more engagement from social media users, but the effectiveness of these techniques in actually explaining the science is unknown. Furthermore, many scientists struggle with adopting these science communication strategies for social media, fearing it might undermine their authority. We conduct a reader study to understand how these science communication techniques on social media affect readers' understanding and engagement of the science. We found that while most readers prefer these techniques, they had diverse preferences for when and where these techniques are used. With these findings, we conducted a writer study to understand how scientists' varying comfort levels with these strategies can be supported by presenting different structure and style options. We found that the side-by-side comparison of options helped writers make editorial decisions. Instead of adhering to one direction of science communication, writers explored a continuum of options which helped them identify which communication strategies they wanted to implement.

CCS Concepts: • Human-centered computing → Collaborative and social computing systems and tools; Social content sharing.

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1 INTRODUCTION

Science communication increases public interest in science by educating, engaging, and encouraging everyday people to participate in the sciences [9, 38]. With the rise of social media, science communication has transitioned away from traditional scholarly articles and towards more informal platforms such as blogs and social media [7, 27, 53]. There is a growing need for scientists to participate in these public forums to bridge the gap between science and everyday people [41, 42].

On social media, science communication strategies emphasize making science engaging and understandable to non-technical audiences and adapt common practices in science communication literature for a social media audience [22]. A study of science communication on Twitter found these strategies: 1) use of a **relatable example** – such as using the iridescence of bubbles to motivate the topic "Thin Film Interference" in physics, 2) use of a **step-by-step** walkthrough that uses 10-12 tweets which use an example to explain every step, and 3) use of **personal language** – the writer talking about themselves and their experience, often in a personal and conversational way, "*Crazy, right? WTH was I thinking* ?!?" [20].

But previous work has not evaluated whether these science communication techniques on social media (example, walkthrough, and personal language) are actually helpful in helping everyday people learn about science. As such, we conduct a study of non-technical readers' rating of STEM explanations with and without each of these three social media explanation techniques to understand how each factor impacts making science explanations engaging and understandable. To facilitate fair comparisons between each condition, we use an LLM to generate science explanations for 15 topics: 5 STEM fields, each with 3 topics at different levels of complexity. Readers evaluated them for understanding and engagement. Overall, readers preferred explanations with examples over no examples and personal language over no personal language. However, readers were split between narratives with and without walkthroughs; certain topics were more suitable for narratives without a walkthrough. Even for techniques they did prefer, readers' personal experience complicate why some preferred narratives without a given technique. There is no one-size-fits-all approach to science communication on social media.

As such, it's important to support STEM experts in navigating diverse audience preferences and help them engage with science communication on social media. Many STEM experts are eager to communicate to the public [16]. But many scientists are not trained in how to translate complex technical topics for an everyday audience and struggle to motivate and explain topics to people beyond their expertise [53]. Furthermore, studies find that scientists are hesitant in adopting science communication strategies for social media because inaccurate interpretations or misrepresentations of their work could affect public understanding and their own reputations [21, 35]. Scientists often feel conflicted over their personal and professional identities when engaging in science communication on social media [30].

We explore how to accommodate different writers' comfort levels when it comes to adopting science communication strategies for social media. We ran an in-depth 2-hour study of writers (n=10) who were given three initial draft options with different narrative structures (*One Example*, *No Example*, and *Many Examples*) and selected one draft to move forwards with. Then, writers saw the selected narrative presented *With Personal Language* and *Without Personal Language*. We found that while many writers maintained their beliefs about how science should be communicated, seeing options side-by-side helped them recognize effective and ineffective science communication techniques, ultimately helping them make editorial decisions regarding what to cut, edit, and merge. Furthermore, when presented with science explanations with and without personal language, scientists often chose to merge lines of dialog between the different conditions. Overall, this shows there is continuous design space for structure and style options in public science

communication. Writers can be aided by seeing points in the design space and finding a place they are comfortable with on the continuum.

We conclude with a discussion of how to mediate between audiences' needs for understanding and engagement and accommodating writers' hesitancy around loss of authority and oversimplification of science.

2 BACKGROUND ON TWEETORIALS

Tweetorials are a form of social media science communication on Twitter, defined as a chronological series of tweets that explains a science topic [8, 49]. According to Breu and Berstein, Tweetorials emerged from the medical community to continue education for other medical professionals, often containing medical jargon and not intended for everyday audiences. As the form became popularized, other communities on Twitter began to adopt the format [6, 8, 49]. As a result, Breu's definition of a Tweetorial, "a collection of threaded tweets aimed at teaching users who engage with them," can be applied to various domains such as biology, computer science, and economics.

Gero et. al. identified and compared key features of Tweetorials to traditional science communication strategies [21]. The authors identified 3 main structural components of Tweetorials to be the hook, body, and conclusion. Previous research has explored strategies for writing engaging hooks [33, 34]. Thus, we focus on specific strategies that appear within the body of a Tweetorial.

2.1 Key Strategies of the Tweetorial Body

According to Gero et. al., the body of a Tweetorial is the most varied in length and types of detail used to explain a given topic [21]. The researchers found that Tweetorials contain specific techniques such as the use of an example, a step-by-step walkthrough structure, and personal language.

2.1.1 Example (E). Like traditional science communication, Tweetorials often contain an example that uses familiar or simpler concepts to explain the main idea [21]. We define this as an **example (E)** technique. Components of the example are the *use case* and the *scenario*. The *use case* is a general application of the scientific topic and the *scenario* is a specific situation that describes how the science topic was applied. For example, one Tweetorial uses the example of fingertips getting wrinkly in the bath to explain water immersion wrinkling. For this Tweetorial, the use case is when fingers get wrinkly in water. The scenario is a parent bathing their child. We use the use case and scenario for more finegrain control over the LLM-generated narratives in Section 4.2.

2.1.2 Walkthrough (W). Tweetorial structures often use a narrative and signposting to establish a narrative structure. We define these two attributes as the walkthrough (W) technique. Narrative is defined by a series of connected events to explain a given topic. Tweetorials signpost by using transition words like "Firstly" and "Secondly," or by using a list of questions to help frame the sequence of the Tweetorial. In a Tweetorial about selectivity metrics in college rankings, the author uses the second tweet to list out 3 driving questions for the explanation and to establish the structure of the Tweetorial: "1. Does "selectivity" actually tell you anything useful about how good your education will be? 2. What does "selectivity" actually measure that is of value to a student? 3. Why do I have the feeling somebody chose this metric cause they just needed more stuff to rank by?"

 $^{^{1}}http://language-play.com/tech-tweets/tweetorial/4\\$

²http://language-play.com/tech-tweets/tweetorial/14

2.1.3 Personal Language (P). Tweetorials often use subjective, conversational, and informal language. We define these features as the **personal language** (P) technique. Some authors might use first-person pronouns like "I" to talk from their subjective perspective,³ or use the second person, "you," to directly address the audience in conversation: "You can think of a Hash Function like a magic fingerprint reader." Some authors might use ALLCAPS or emojis to engage in informal language and humor: "OH MAN MY HEAD HURTS AND MY LIMBS TINGLE EVERY TIME I GO TO A CHINESE RESTAURANT, I THINK IT MAY BE ALL THE MSG THEY PUT IN THE FOOD???". 5

Figure 1 provides an annotated Tweetorial highlighting these three techniques (example (E), walkthrough (W), and personal language (P)) on the topic of Walker's Action Decrement Theory in Psychology to demonstrate how they are applied in a science explanation. We use these three techniques to ground our approach in understanding reader preferences for science communication on social media and how writers explore the design space for science writing structures and styles.

3 RELATED WORK

3.1 HCI for Science Communication

Science communication is integral to engage everyday people in science advancements and help them understand the world around them. Research has explored how new forms of science communication, such as Tweetorials, are situated among other genres, how different social media platforms shape the expectations that readers have, readers' interaction behaviors with science writing, and the way readers access scientific information [24, 25, 50, 53].

Science communication on social media is informal and often told from a personal perspective to engage a broader audience [21]. Previous work has compiled recommendations for effective science communication on social media based on how likely using these strategies will increase engagement: comments, likes, and shares [5, 19, 58]. But these works do not consider whether these techniques are actually effective for readers to understand the science. Our work evaluates whether these different science communication strategies on Twitter are effective in helping readers engage with and understand the science.

For scientists seeking to engage with science communication on social media, they struggle to understand their "audience" which consists of readers from diverse backgrounds, levels of scientific literacy, and preferences which makes it challenging for scientists to determine *who* they are writing for [44, 46, 53]. Furthermore, each social media platform has its own set of community norms and demographics [39, 45]. Research has also shown how scientists struggle to reach non-research audiences on social media and to adapt to these new genres of science communication [14, 30, 31, 35]. Even though language with strong sentiment can predict success on social media, many scientists are hesitant about such language having negative effects on their credibility [22, 56, 57]. We use these findings to explore how providing different structure and style options to writers can help accommodate different writers' hesitancy and comfort levels with science communication on social media.

 $^{^3} http://language-play.com/tech-tweets/tweetorial/1\\$

⁴http://language-play.com/tech-tweets/tweetorial/31

⁵http://language-play.com/tech-tweets/tweetorial/33

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Fig. 1. Annotated Tweetorial on the topic of Walker's Action Decrement Theory in Psychology with color highlights corresponding to Example, Walkthrough, and Personal Language.

3.2 LLM-based Writing Support

Recent advances in AI writing capabilities have accelerated work in LLM-based writing interfaces [4, 10, 32, 47, 48]. Our contributions are most directly tied to the specific writing task of drafting (writing stage) science narrative explanations (purpose) for an everyday audience (audience) [32].

Previous research has explored how analogies can be used to translate technical content into more relatable references for people [1, 28, 29, 37]. LLM-based systems have been used to explore different ways to generate engaging and relatable hooks for science narratives [33, 34]. LLMs have been used for the personalization of scientific information to improve comprehension, alignment to individual preferences, and accommodate different science literacy levels [2, 15, 17]. But these cases focus on generating relatable examples or translating technical jargon into everyday language and do not connect the corresponding examples to an overarching narrative to explain the science.

LLMs have been used in narrative generation to support story writing by tailoring generated narratives to user inputs such as story elements, topics, or rough sketches of plot development [3, 11, 40, 43]. New methods have explored ways to improve coherence in LLM-generated long-form story content through recursive prompting and revision and outline control [52, 54, 55]. While advancements have been made in improving coherence in LLM-generated long-form stories, generalizing these methods to science narratives is hard. Science narratives need both a coherent story and an accurate representation of the science. Our work explores how LLMs can support scientists in drafting a science narrative. To do so, we bridge research in relatable example generation with story narrative generation to create science narratives that follow a cohesive narrative structure around a relatable example. We provide scientists a baseline science narrative to iterate on.

4 READER STUDY: METHODOLOGY

4.1 Research Questions

Tweetorials typically include three techniques **example (E)**, **walkthrough (W)**, and **personal language (P)** [21]. We want to understand how each of these techniques affects readers' ratings of science communication on social media. Given that most published Tweetorials contain these three techniques, we hypothesize that science explanations that contain all three features, **EWP**, will have the highest reader preference rating. To evaluate the effect of the 3 different features, we compare narratives with all three features (**EWP**) to narratives with one of the features removed (**EW**, **EP**, **WP**). We investigate the following hypotheses in a survey study with readers:

H1: Example (E): Readers prefer explanations with an example (EWP) compared to those without an example (WP).
H2: Walkthrough (W): Readers prefer explanations that include a step-by-step walkthrough of the topic using an example (EWP) compared to explanations with multiple unrelated examples (EP).

H3: Personal Language (P): Readers prefer explanations that use personal and subjective language (EWP) compared to explanations that have a neutral scientific voice (EW).

Testing each of these hypotheses requires comparing two explanations for the same scientific topic that are as similar as possible and only vary in whether they contain a example, walkthrough or personal language. Parallel examples like this are unlikely to occur naturally. Thus, we use AI to generate parallel explanations in each condition (See Section 4.2).

4.2 Automatic Narrative Generation Strategy

We used OpenAI's GPT-4 API to generate science explanations with and without each technique in the form of Tweetorials (about 10 tweets in length) to ensure consistency and to make fair comparisons between science explanations. We describe the method for each technique in Sections 4.2.1, 4.2.3, and 4.2.2.

We cover 5 diverse STEM fields: a physical science field (Physics), a social science field (Psychology), a technological field (Computer Science), a mathematical field (Statistics), and an engineering field (Civil Engineering). For each field an expert selected topics for 3 different levels of complexity (introductory, intermediate, and advanced levels) for a total of 15 topics (Appendix A). We generated 75 different science explanations (5 conditions for each topic) for readers to rate. Each science explanation was validated by a corresponding expert for accuracy. We describe exact prompting methods for each hypothesis (H1: Example (E), H2: Walkthrough (W), H3: Personal Language(P)) below.

4.2.1 Generating Tweetorials with and without Examples (H1). We used GPT-4 to generate science narratives that contain an Example, Walkthrough, and Personal language. We included five few-shot examples of published Tweetorials on Twitter to create our experimental condition: EWP. Experts on each topic provided data inputs [use case] and [scenario] (described in Section 2.1.1) to define the specific example the given narrative should use throughout the explanation. We provided specific guidelines regarding how the LLM should incorporate the given example, a walkthrough, and personal language. We iterated on each line separately and in compilation to ensure that the prompt was concise, essential, and reasonably consistent (Appendix B).

To generate the baseline condition, **WP**, we use a "remove" method which provides GPT-4 a given narrative and a set of guidelines that specifies what technique to remove from the given narrative while maintaining all other conditions. The output is a new narrative with only the specified technique removed. To generate a science narrative without an example, we use the "remove" method on the example. We pass in the experimental condition narration, **EWP**, and a set of guidelines that specify only the example should be removed from the narrative while maintaining all other elements such as structure and style (Appendix B.2). We use this same prompting strategy to "remove personal language" in Section 4.2.2.

Figure 2 shows a side-by-side annotated example of the experimental condition (EWP) and baseline condition (WP) for the topic of Walker's Action Decrement Theory. The lack of example highlights in green in the baseline condition shows the effect of no example in contrast with the explanation with everything.

4.2.2 Generating Tweetorials with and without Personal Language (H3). To understand reader preferences for science explanations with and without personal language (H2:Personal Language), we followed a similar GPT-4 generation protocol as in Section 4.2.1 to generate the experimental condition which contains all three techniques and few-shot examples, **EWP**. To generate the baseline condition, we used the "remove" procedure from Section 4.2.1 to "remove personal language" from the experimental condition, *EWP*. We pass in *EWP* and specify guidelines to only remove the personal language while maintaining all structural elements of the science explanation to create **EW**.

Figure 3 shows a side-by-side annotated example of the experimental condition (EWP) and baseline condition (EW) for the topic of Walker's Action Decrement Theory. The lack of personal language highlights in yellow in the baseline condition shows the effect of removing personal language from EWP.

4.2.3 Generating Tweetorials with and without Walkthroughs (H2). To understand reader preferences for walkthroughs (H2:Walkthrough), we used GPT-4 to generate two different science explanations with contrasting narrative structures. In preliminary testing, we found that the "remove" method failed to generate narratives without walkthroughs because

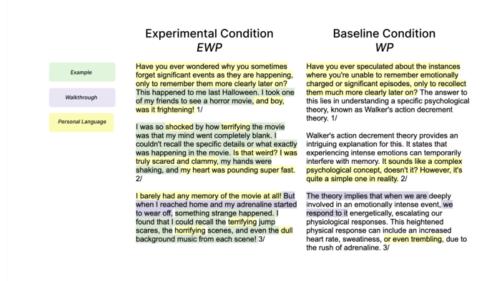


Fig. 2. **H1: Example** Sample explanation generations on the topic of "Walker's Action Decrement Theory" in Psychology comparing the experimental condition (EWP) and baseline condition (WP).

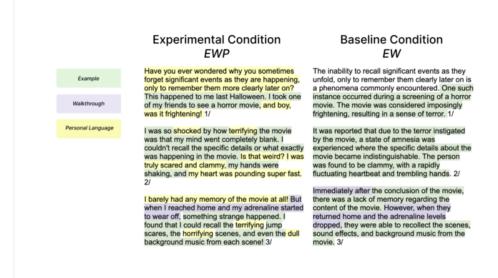


Fig. 3. **H3:Personal Language** Sample explanation generations on the topic of Walker's Action Decrement Theory in Psychology comparing the experimental condition (EWP) and baseline condition (EW).

Baseline Condition Experimental Condition EWP-NoFewShot EP-NoFewShot Think of the weights in an Al model like the dials on a sound mixer. Backpropagation is like a sound engineer, constantly fine-tuning the As with backpropagation, each mistake is a stepping stone to perfection. Every failure brings it closer to the goal. The sweet taste of success, in my case, a perfect batch of cookies, goes beyond the initial hurdles. That's the beauty of dials(weights) based on the difference between the desired output and actual result for improved learning, isn't it? 7/ accuracy, 7/ Just like perfecting a recipe, backpropagation Where does the term 'Backpropagation' come involves constant tweaking and learning until we get the desired output. It's not defeat that defines from? It's because after every prediction, the process sends the error value backward through us, but rather how we respond to it. The machine learns, improves and eventually nails it. Much the network. This 'feedback' enables the Al to adjust its calculations and reduce future errors like our cookie baking endeavor, 8/ Backpropagation in essence is all about learning. improving and iterating. 8/ So, the next time you find yourself stuck in a loop of trials and errors, remember backpropagation, and remember my cookie story. Every effort you make counts, every mistake brings you a step If AI is like a musician learning a new tune backpropagation is the process of listening to playback and realizing which notes need fixing. closer to success. Isn't it fascinating how life mirrors AI? 9/ It's the way Al networks get better at hitting their notes – becoming more accurate in their predictions & responses.9/

Fig. 4. **H2:** Walkthrough Sample explanation generations on the topic of Back Propagation in Computer Science contrasting experimental condition (EWP-NoFewShot) and baseline condition (EP-NoFewShot).

the walkthrough served as the narrative structure. Thus, we provide the data inputs of [topic] and [domain] and a new set of guidelines to GPT-4 to generate narratives without a walkthrough (Appendix B.3). The guidelines specify instructions for not using a walkthrough (e.g. the explanation should use a non-sequential approach and that every tweet stands alone). No few-shot examples were added because there were no published Tweetorials with no walkthrough to create **EP-NoFewShot**.

We used the same base prompt as the experimental conditions in Section 4.2.1 and Section 4.2.3 to generate a science explanation with an Example, Walkthrough and Personal language. To maintain a fair comparison with EP-NoFewShot, we omitted few-shot examples to create EWP-NoFewShot. Figure 4 highlights the differences between science narratives with and without walkthroughs.

4.3 Participant Recruitment

We recruited 35 undergraduate students and recent college graduates who did not study nor intend to study any of the 5 science fields. We chose non-experts because they represent everyday people, who are our target audience for science communication on social media. Because the Tweetorials that we aim to emulate are US-centric in the examples and language used, we disqualified participants who do not self-identify as culturally American and whose first language is not English. The participants are from 12 universities and liberal arts colleges in the United States, with an average age of 22, and a gender distribution of 4 males, 29 females, and 2 non-binary individuals. We distributed the recruitment survey via school mailing lists, Slack workspaces, Discord channels, and snowball sampling [23] among schoolmates of the participants. Each participant was compensated \$27 dollars. The study was approved by our institutional IRB.

4.4 Survey Procedure

Following recruitment, each qualified participant attended an onboarding session with an experimenter on Zoom. The experimenter explained the study procedure and data collection, and acquired participants' consent. The experimenter shared a sample Twitter thread and survey for the participant to answer and explained the Likert-scale rating criteria. The participants thought aloud while answering the sample survey, justified their rating decisions, and asked clarifying questions before completing the survey on their own. Participants' justifications for their ratings on the sample science narratives aligned with the defined definitions.

We implemented our survey on Qualtrics, an online survey platform. On the first page, participants are asked to read a Twitter thread. The page included a one-minute timer to prevent participants from skimming or skipping the reading process. After reading the Twitter thread, the participant advances to the next page and completes four Likert-scale questions that correspond to the four evaluation dimensions (engaging, relatable, understandable, and easy-to-follow, see Section 4.5.1), on the scale from 1 to 5 (1-Strongly Disagree, 5-Strongly Agree). This process repeats 15 times for the 15 science explanations for each participant.

To minimize bias from prior knowledge, we employed a between-subjects design, ensuring that each participant only read each topic once, and no participant read the same topic under two different conditions. Each participant read a randomized selection of Twitter threads across all conditions and topics. Each Twitter thread was evaluated by 7 participants to achieve a statistical distribution and reduce individual bias.

4.5 Data Collection and Analysis

4.5.1 Survey Design. Each science explanation was evaluated on 4 different questions: (1) I find the thread engaging, (2) I find the thread relatable, (3) I find the thread understandable, and (4) I find the thread easy to follow. Engaging refers to the language, while relatable refers to the example used. Understandable refers to the presence of technical jargon, while easy-to-follow refers to the sequence and flow of the narrative. The onboarding session demonstrated that participants were able to differentiate between each of the dimensions. We sum the participant's ratings for each Likert-scale question to create an overall score for the given science explanation (20-point max score).

4.5.2 Data Analysis. Quantitative Analysis: Survey Data

Our main goal was to test whether the inclusion of examples, walkthroughs, and personal language influenced readers' engagement and understanding. We used the overall score (sum of the 4 Likert responses) for the given science explanation in our analysis. Because each participant did not read the same topic twice and sampled across multiple STEM fields, our data exhibited a hierarchical structure: each rating is linked to a specific participant and a specific topic.

We used a Generalized Linear Mixed Model (GLMM) for our analyses. The GLMM framework allowed us to isolate how each technique affected the ratings for each science explanation based on the overall score of the Likert ratings, while statistically controlling for other factors. We can estimate the direction and magnitude of the effectiveness of each technique (examples, walkthroughs, and personal language) relative to explanations without them. We also accounted for individual differences in baseline rating tendencies by including random intercepts for each participant because people may vary in their strictness or leniency when rating explanations. We also included random intercepts for each of the five STEM topics to account for potential differences across fields (e.g., participants might rate Computer Science explanations differently than Physics explanations). The GLMM model allowed us to compare pairs of explanations—those with a

given technique versus those without—to determine whether the presence of each technique had a significant effect on the ratings.

Qualitative Analysis: Followup Interviews To gain more nuanced insights into participant preferences in the survey data, we randomly reached out to 17 of the 35 participants for follow-up interviews. 8 of 17 participants opted-in for a 15-minute follow-up interview on Zoom. The participants are compensated \$10 total. In the follow-up interview, we asked the participants to re-read a science explanation they had previously read and explain in detail specific instances from the science narrative that influenced their Likert ratings. The interviews were recorded and transcribed before three researchers conducted a thematic analysis. We used grounded theory to derive insights from the interview transcripts [12]. The first author read through all interview transcripts, inductively derived a preliminary set of codes, and then grouped the codes based on themes. The first author and two additional authors collaboratively reviewed and refined the themes until a consensus was reached.

5 RESULTS: READER STUDY

5.1 Quantitative Findings on Survey Data

Overall, we collected 105 ratings on 75 different science explanations. This consisted of 35 different annotators who evaluated each science explanation on 4 different Likert-scale questions. We conduct a quantitative analysis of the survey data followed by a qualitative analysis of individual reader's preferences for science communication to contextualize nuances to the quantitative data.

5.1.1 Usage of Example Preferences. To evaluate H1:Example, we compare experimental condition EWP to baseline condition WP. We found that participants prefer reading explanations with an example (EWP) over without an example (WP). The results presented in Table 1 illustrate the effects of the two conditions on the total score of the four survey questions (max 20 points) within a Generalized Linear Mixed Model (GLMM) framework. The experimental condition, EWP, received a score of 15.831 which shows a statistically significant increase in user preference when compared to the baseline condition of 13.003 (p < 0.0001). The effect size is 2.828 which shows that readers rated narratives with an example (EWP) almost 3 points higher than narratives without an example (WP). Additionally, the random effects analysis reveals a large group variance of 2.626 suggesting the differences among individual participants play a significant role and a small fields variance at 0.062, the specific field of study has a minimal impact.

Effect	Score (max. 20)	Coefficient	Standard Error	z-value	p-value
Intercept[WP]	13.003	13.003	0.483	26.937	
CONDITION[EWP]	15.831	2.828	0.546	5.183	0.000
Random Effects					
Group Variance		2.626	0.752		
Fields Variance		0.062	0.543		

Table 1. GLMM Results for H1:Examples

5.1.2 Step-by-Step Walkthrough Preferences. To evaluate H2:Walkthrough, we compare experimental condition EWP-NoFewShot to baseline condition EP-NoFewShot. We found that readers had a slight preference for explanations with a walkthrough compared to without a walkthrough, with a considerable variance on the fields of study. Table 2

summarizes the findings from a GLMM analysis. The experimental condition, EWP-NoFewShot received a score of 15.965 which was not statistically significant compared to 14.729, the baseline score for EP-NoFewShot (p = 0.057). As such, there is no significant difference in how readers rated explanations with and without walkthroughs. The random effects analysis shows a minimal group variance of 0.002, indicating little variability among participants. However, the field variance is considerable at 2.566, suggesting that participants prefer having a walkthrough for some STEM topics but prefer having no walkthrough for other STEM topics. Our qualitative findings (Section 5.2) provide further explanations on why some participants are divided in their preferences for walkthrough.

Table 2. GLMM Results for H2:Walkthrough

Effect	Score (max. 20)	Coefficient	Standard Error	z-value	p-value
Intercept[EP-NoFewShot]	14.729	14.729	0.439	33.537	
CONDITION[EWP-NoFewShot]	15.695	0.966	0.508	1.902	0.057
Random Effects					
Group Variance		0.002	0.618		
Fields Variance		2.566	0.506		

5.1.3 Personal Language Preferences. To evaluate H3:Personal Language, we compare experimental condition EWP to baseline condition EW. We found that participants prefer reading explanations with personal language over without personal language. Table 3 summarizes the findings from a GLMM analysis. The experimental condition, EWP, received a statistically significantly higher score of 15.883 compared to 13.973 for the baseline condition, EW (p < 0.0001). The effect size is 1.910 which means that readers rate explanations with personal language almost 2 points higher than explanations without personal language. Additionally, there is a group variance of 1.392 indicating a moderate level of variability among participants and a fields variance of 1.361 showing a moderate variance among STEM topics.

Table 3. GLMM Results for H3:Personal Language

Score(max. 20)	Coefficient	Standard Error	z-value	p-value
13.973	13.973	0.463	30.175	
15.883	1.910	0.526	3.632	0.000
	1.392	0.717		
	1.361	0.548		
	13.973	13.973 13.973 15.883 1.910 1.392	13.973 13.973 0.463 15.883 1.910 0.526 1.392 0.717	15.883 1.910 0.526 3.632 1.392 0.717

5.2 Qualitative Findings on Reader's Preferences

Overall, participants preferred science explanations with an example over no example and with personal language over no personal language. However, participants were split on the their preference for narratives with and without walkthroughs. We use semi-structured interviews to gain further insights into the reasons why participants might prefer narratives with or without an example, walkthrough, and personal language.

5.2.1 Most Readers Preferred Examples. Overall, readers reported that having an example was helpful. 4 of 8 readers stated the example helped them understand the importance of a topic (P2, P4, P7, P8). 5 of 8 found that examples helped them reflect and understand their own experiences better (P1, P2, P3, P4, and P7). When reading a science explanation about the computer science topic of depth-first search, P2 remarked that learning how the algorithm can be applied to navigating a maze helped her engage with the topic: "I don't really care about computer science algorithms, but I do care about how this applies to my own life."

However, not all readers needed an example to help them understand the topic. 3 of 8 participants mentioned how the example felt unnecessary and detracted from the content of the explanation (P1, P2, P8). When reading about depth-first search, P1 mentioned how the given example of navigating through the Botanical Garden felt unnecessary: "The concept in and of itself is interesting. I would have just read about that. I don't really need any more context." For P8, when learning about thin film interface through the example of a child playing with bubbles, he remarked that "[the example] doesn't really pertain to me in any way," demonstrating how certain examples might not resonate with particular audiences.

3 of the 8 participants mentioned how they would reference their own experiences to help ground the technical explanation (P1, P2, P4). When P2 was reading about thin film interference without an example, she used her own experience in working with glass to ground her understanding of the topic: "[the topic] was really relevant to my life and what I'm already doing." For P4, when the given example of watching a horror film was used to explain Walker's Action Decrement Theory, she mentioned how even though the example was unrelatable, she referenced her own experiences to find an example that fit the same context. This shows that readers use their own experiences to contextualize the science for explanations that do not include an example or that include an example unrelatable to the reader.

5.2.2 Readers had No Preference for Narratives with Walkthroughs. There was no statistical significance in our results comparing reader preferences for narratives with and without walkthroughs. In this section we will investigate why some readers prefer walkthroughs or no walkthroughs.

Some readers reported that the walkthrough helped establish a structure for the explanation (P2, P3, P8), provide evenly paced information (P1, P3, P6), and helped them follow through with the science (P4, P6, P7). P3 appreciated the walkthrough for the topic of Walker's Action Decrement Theory in Psychology because it helped them understand how their heightened emotional state when watching a horror movie might affect their memory. By walking through 3 different stages of the narrator's emotional journey during this event and how it affects their memory, P3 mentioned how the narrative helped "set the stage" and "allows you to follow through with [the science explanation]." The walkthrough provided a scaffold to support the reader in processing the information as a sequence of events.

But not all readers preferred narratives with a walkthrough. 3 participants (P2, P3, P7) reported that the walkthrough structure made the explanation feel overly explanatory or repetitive. For the topic of Walker's Action Decrement Theory, P2 said that the walkthrough narrative was "just overly explanatory for a concept that is very intuitive," demonstrating how for certain topics a walkthrough might not be necessary.

4 participants (P2, P4, P5, P6) preferred science explanations without a walkthrough but with many examples because they provided multiple different angles to view a topic in a condensed space. P4 stated that the explanation without a walkthrough broke down the topic of the curtain wall system into smaller, self-contained chunks of information that made reading the explanation "less intimidating." For example, one paragraph of the explanation focused specifically on the aspect of temperature control, while the subsequent paragraph explored the structural construction of the curtain wall. P4 said that having the information broken down in this way made it more "digestible" to learn about the topic.

For P6, the "list of facts" structure of explanation without a walkthrough helped them gain a broad overview of the topic. This illustrates that for some topics, readers might not want an in-depth walkthrough of the science and might prefer getting a high-level overview of how the science works.

5.2.3 Personal Language Sometimes Distracts from the Science. Overall, readers preferred reading explanations with personal language. Participants reported that the personal language helped establish a writer/reader connection (P1, P3, P5). But not all readers preferred narratives with personal language. 2 readers preferred reading science explanations with no personal language because they believed personal language was unnecessary (P1, P8): "[the explanation is] full of fluff coming from a personal perspective that I didn't really care about" (P1). P8 mentioned that he did not need personal language for engagement when reading about science, additionally, he hypothesized that other readers "[might] need the personal aspects to get them to read something that they wouldn't otherwise be interested in." Depending on a reader's inclination towards science, personal language may or may not be necessary to help them engage with these science narratives.

6 WRITER STUDY: METHODOLOGY

The reader study found that overall readers had no preference between narratives with and without walkthroughs but did prefer when explanations had multiple different examples to explain the topic. Previous studies have shown that scientists often struggle with two aspects of science communication on social media (1) framing science for everyday audiences and (2) using informal language to communicate science [30, 53]. As such, we provide writers with different options to structure and frame their writing (*One Example, No Example, Many Examples*) and provide options to see their narrative with and without personal language to support the writing process for social media science communication. Our research questions are:

RQ1: How does seeing structure options (*One Example, No Example, Many Examples*) help writers consider different framing strategies for writing science for social media?

RQ2: How does seeing style options (*With Personal Language*, *Without Personal Language*) help writers consider different communication styles when writing science for social media?

6.1 Participants

We recruited 10 PhD-level researchers interested in communicating their research to the public on social media. Participants are from 2 universities, an average age of 25, with a gender distribution of 9 males and 1 female (Table 4). We advertised the study to students in research labs through school mailing lists, Slack workspaces, and snowball sampling among lab mates of the participants. Their expertise spans various CS research areas, including natural language processing, programming languages, and social computing. The study was conducted over Zoom and took approximately 2 hours. Each participant is compensated \$40 dollars total. The study was approved by our institutional IRB.

6.2 Writing Study Procedure and Analysis

6.2.1 Study Procedure. Each session includes a pre-study presentation, an interface demonstration, and two writing sessions with a 15-minute break in between. The experimenter used a short presentation to educate participants about science communication on social media, a background on Tweetorials, and different techniques and examples for

ID	Field of Expertise	Research Experience (years)
1	Computer Science and Journalism	2
2	Artificial Intelligence and Neuroscience	2
3	Human-Computer Interaction	2.5
4	Natural Language Processing	2
5	Natural Language Processing	3
6	Programming Languages	5
7	Computer Security	2.5
8	Quantum Computing	3
9	Human-Computer Interaction	3
10	Computer Science Education	7

Table 4. Participant Demographics for Writer Study

science communication on social media. Next, the experimenter demonstrated the study web interface and explained how it worked.

When the participant was ready for the writing session, the experimenter shared with the participant a URL link to the study web interface. The experimenter started screen and audio recording upon the participant's verbal consent. Participants use the study interface once for each writing session: first to write about the predetermined topic of merge sort and then to write about a topic of their choice. The experimenter implemented think-aloud protocol and encouraged the participant to voice their thought process, reasoning behind their structure and style choices, and editing decisions. After each writing session, the experimenter conducted a semi-structured interview with the participant to understand how seeing different structures and styles influenced their writing choices. Some sample questions are: How did you arrive at your choice of structure/style? How did seeing the options change your preference of structure/style? How have reading the unselected options help you decide which direction to write in?

6.3 Study Interface

We built a web interface that guides writers through a workflow with LLM generations and editing functionalities (Figure 5, Figure 6, Figure 7). The workflow includes the following 4 steps:

Step 1: Structure Options Users first enter their domain and topic to generate the 3 different structure options. After the generation, 3 columns are displayed side-by-side with the corresponding LLM prompts: *One Example, No Example,* and *Many Examples* (Figure 5. The user chooses one of the three to proceed with. Writers can merge certain paragraphs from two structure options by copying and pasting between the columns before proceeding.

Step 2: Selected Structure Feedback and Edits The second part of the interface (Figure 6) allows the writer to iterate on the selected structure by providing feedback instructions to an LLM or making manual edits directly in the textbox (copy, paste, delete, and type). The writer is asked to focus only on editing structural aspects of the text such as technical accuracy, content, and sequence. When they are satisfied with the structure, they proceed to the next step.

Step 3: Language Style Options The third part of the interface compares different style options, it has 2 columns displayed side by side (Figure 7). On the left is the writer's selected and edited draft from the previous step which contains personal language and the right is the draft without personal language. Writers select which narrative they want to proceed with to the next step. Writers can merge certain paragraphs from both options by copying and pasting between the columns before proceeding.

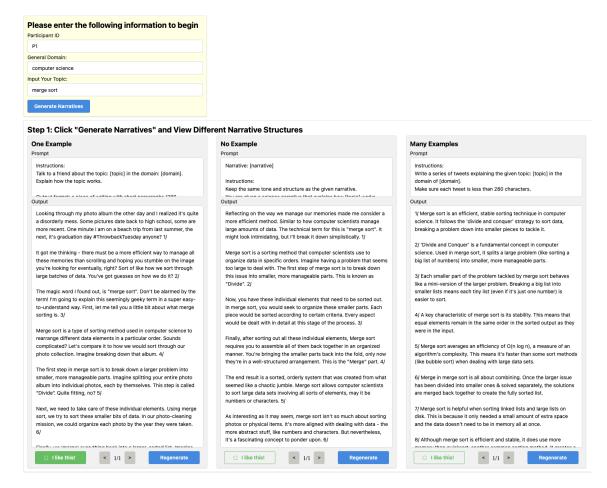


Fig. 5. Study interface: Viewing different structure options (1st of 3 steps)

Step 4: Final Edits The last part of the interface displays the draft from Step 3 (not shown). The writer refines and finalizes the writing until they are satisfied and ready to share it on social media.

6.3.1 Data Analysis. We analyze interview transcripts and video recordings to understand quantitative and qualitative aspects of participants' choices and reasoning when presented with different options. We analyzed participants' choice of structure (One Example, No Example, Many Examples) and style options (With Personal Language and Without Personal Language), participants' editing actions and LLM feedback prompts, iterations of writing generations and refinements, as well as the final writings.

One researcher independently conducted a bottom-up, open-coding approach to data analysis [12]. Then, the researcher worked with two other researchers to iterate on the codes, discuss their similarities and differences as part of a comparative analysis [36], and leveraged them in an affinity diagramming process [26]. The researchers determined that they reached code saturation when no researcher could identify new codes or arrive at new interpretations.

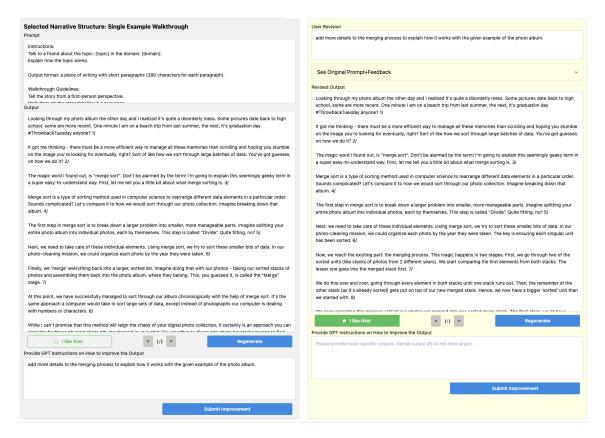


Fig. 6. Study interface: Editing narrative structure (2nd of 3 steps)

7 RESULTS: WRITER STUDY

7.1 RQ1: Different Narrative Structures help Writers Choose Appropriate Framing Techniques

Of the three narrative choices (*One Example, Many Examples, No Examples*), most science explanations used the *One Example* narrative to iterate on (9 of 20). The second most chosen narrative strategy was merging components between the *One Example* and *Many Examples* options (5 of 20). The *Many Examples* strategy was chosen 4 of 20 times. The least used structure was *No Examples* (2 of 20). Choices made by participants and topic are found in Table 5. Writers' choices differed depending on the topic, their personal preferences for science communication, and whether or not they had a predefined explanation structure they wanted to follow. The *One Example* option often provided writers with a clear sequencing of information to follow. Some participants (P2, P4, P6, P10) chose to merge between the *One Example* and *Many Examples* and used examples covered in the *Many Examples* option to supplement certain explanations in the *One Example* narrative. Occasionally, the *No Example* option providing a strong technical explanation for writers to build off of.

Seeing different narrative structures helped 7 of 10 writers identify their own preferences for science communication by solidifying or challenging their existing beliefs (P2, P3, P5, P7, P8, P9, P10). P9 mentioned that seeing the narrative with *Many Examples* helped him solidify his initial feeling that "one example is a good way to engage people." But

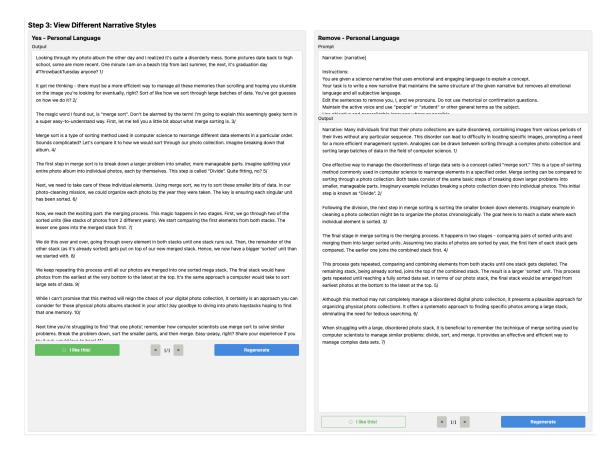


Fig. 7. Study interface: Viewing different style options (3rd of 3 steps)

P7 mentioned how seeing multiple structure options helped him re-evaluate his initial approach to explaining the topic of word embeddings. P7 initially wanted to use the *One Example* narrative structure, but instead chose to use the *Many Examples* narrative because the structure provided for the topic of word embeddings: "I was able to see what other things I might actually want to include when I'm trying to explain it, and what other possibilities there are for explaining."

Seeing multiple narrative structures helped 4 of 10 writers merge different framings of a topic (P2, P4, P6, P10). For multiplicative weights update, P10 merged elements from *Many Examples* into a base narrative with *One Example* to emphasize the dimensions of online learning and regret minimization which are "important facts about the topic, but wasn't brought up in the [*One Example*] option." Because the *Many Examples* option provided him with different angles to motivate or contextualize the topic, the selected paragraphs from *Many Examples* could be "slotted in at the end."

There were 4 times where writers already had an established outline in mind for how to write the science explanation for one of their two topics (P1, P3 P8, P9). But for most writers and topics, seeing different options provided 8 of 10 writers an example of what to avoid when explaining science to an everyday audience (P1, P2, P3, P5, P6, P7, P8, P9). Seeing the *No Example* option helped them consider their audience's technical ability and the background needed to

explain the science. P6 said *Many Examples* narrative had a "rigorous depiction of what the software is, [which can be hard] for a general audience to imagine what that means."

Participant ID	Domain	Topic	One Example	No Example	Many Examples	Merged
P1	Computer Science	Merge Sort			✓	
PI	Statistics	Gradient Linear Additive Models	✓			
P2	Computer Science	Merge Sort				Primary: One Example (Secondary: Many Examples)
	Computer Science	Gradient Descent	✓			
Р3	Computer Science	Merge Sort		✓		
P3	Qualitative Analysis	Ordinal Regression		✓		
P4	Computer Science	Merge Sort				Primary: One Example (Secondary: Many Examples)
P4	Natural Language Processing	Controlled Decoding				Primary: Many Examples (Secondary: One Example)
P5	Computer Science	Merge Sort	✓			
P5	Natural Language Processing	Word Embeddings			✓	
	Computer Science	Merge Sort	✓			
P6	Programming Languages	Formal Verification				Primary: One Example (Secondary: Many Examples)
De.	Computer Science	Merge Sort	✓			
P7	Natural Language Processing	Embedding Space			✓	
P8	Computer Science	Merge Sort	✓			
P8	Quantum Algorithms	Grover's Algorithm			✓	
P9	Computer Science	Merge Sort	✓			
19	Tangible User Interfaces	4D Printing	✓			
	Computer Science	Merge Sort	✓			
P10	Optimization Algorithms	Multiplicative Weights Update				Primary: One Example (Secondary: Many Examples)
		Total Count:	9 One Example	2 No Example	4 Many Examples	5 Merged

Table 5. Participants, the topic they wrote on, and the corresponding narrative structure that they chose. When merging two narratives, "primary" denotes the narrative structure that the participant used as the base and "secondary" means that the writer incorporated elements from this narrative into the primary narrative.

7.2 RQ2: Different Style Options Help Writers Balance Personal Preferences with Social Media Communication

The most common narrative strategy that writers used was *With Personal Language* (12 of 20). Merging elements from the *With Personal Language* and *Without Personal Language* style was the second most common action that writers performed (6 of 20). Only 2 of 20 narratives used narratives without personal language. Overall, writers prefer using science narratives that include personal language and editing the LLM-generated language to match their own voice. Many writers found that comparing between narratives with and without personal language helped them identify and adopt useful techniques they might not have otherwise used in their own writing.

8 of 10 participants chose to begin with the *With Personal Language* option because seeing personal language provided a more accessible base narrative that writers could use to edit or replace style elements (P1, P2, P3, P5, P6, P8, P9, P10). Seeing the placement of personal language helped P6 identify where and what to edit instead of determining where and what to add if he was working from the *Without Personal Language* option: "I try and get a pretty good baseline, and the personal language involved adds to the baseline." Furthermore, seeing options with personal language helped writers appreciate language that they might not have thought of using and internalize the importance of these style

choices when read in juxtaposition with a narrative without personal language. For P7, seeing GPT-generated personal language helped him adapt to the genre of science communication on social media: "I think the enthusiasm, while it may not necessarily be the way that I would have written this, feels like it's a more engaging way of trying to explain this to people on the internet."

But for 2 of 10 writers, starting from the narrative *Without Personal Language* helped them evaluate the technical content of the explanation before adding back personal language (P2, P3). P2 mentioned how he prefers the remove personal language option because it is a "simpler version" that he can add his own writing voice to, instead of editing GPT's writing voice. P3 mentioned that she chose to start with the narrative *Without Personal Language* because she valued the content explanation over the personal language: "I do like being more objective and professional when writing explanations about scientific concept."

Participant ID	Domain	Topic	With Personal Language	Without Personal Language	Merged Narrative Styles
P1	Computer Science	Merge Sort	✓		
r i	Statistics	Gradient Linear Additive Models			Primary: Without Personal Language
P2	Computer Science	Merge Sort		✓	
FZ	Computer Science	Gradient Descent			Primary: With Personal Language
P3	Computer Science	Merge Sort			Primary: With Personal Language
13	Qualitative Analysis	Ordinal Regression			Primary: Without Personal Language
P4	Computer Science	Merge Sort	✓		
F4	Natural Language Processing	Controlled Decoding	✓		
P5	Computer Science	Merge Sort	✓		
гэ	Natural Language Processing	Word Embeddings			Primary: With Personal Language
P6	Computer Science	Merge Sort	✓		
го	Programming Languages	Formal Verification	✓		
P7	Computer Science	Merge Sort			Primary: With Personal Language
Γ/	Natural Language Processing	Embedding Space	✓		
P8	Computer Science	Merge Sort	✓		
10	Quantum Algorithms	Grover's Algorithm		✓	
P9	Computer Science	Merge Sort	✓		
F9	Tangible User Interfaces	4D Printing	✓		
P10	Computer Science	Merge Sort	✓		
1 10	Optimization Algorithms	Multiplicative Weights Update	✓		
		Total Count:	12	2	6
		Iotai Count:	With Personal Language	Without Personal Language	Merged

Table 6. Participants, the topic they wrote on, and the corresponding narrative style that they chose. For merged narratives, "primary" denotes the narrative style that the participant chose as their base narrative, and writers incorporated elements from the remaining style option into the primary narrative.

8 DISCUSSION

8.1 The Importance of Narratives in Science Communication

Overall, the use of an example was helpful for most readers. An example helped frame the science and provide readers a grounding for the science explanation. For certain topics, readers also enjoyed reading multiple different examples to gain an understanding of the topic through multiple perspectives. Overall the use of one or many examples was beneficial to most readers, the effectiveness of these strategies vary by reader. Some readers replace or augment science explanations with examples from their own life when the example used is unrelatable or missing. Some readers do not want an explanation at all. Different readers need different strategies to help them engage with and understand the science.

To account for varying audience preferences, we provide writers with different narrative structures to help them recognize which narrative strategy was most suitable for a given topic. Instead of having to recall science communication

strategies, writers could rely on the generated structure options to identify the effective techniques that were used and merge techniques across different options. This finding connects with the design principle of recognition over recall and echoes findings from the reader study: writers benefit from seeing different narrative strategies [18]. This scaffolding technique for writers' decision-making also exposed them to narrative structures they might not have considered and enables them to combine different structures to align better with their goals. Building off literature in constraint-based creativity, we provide writers with 3 distinct options to create a constraint space that encouraged writers to merge elements across different strategies [13, 51]. We found that presenting different options for narrative structures helped some writers shift perspectives on how to communicate science on social media.

8.2 Presenting Personal Language as a Continuum and not a Binary

Previous research has found that scientists often feel conflicted over their personal and professional identities when engaging in science communication on social media [30]. Some scientists are hesitant to use colloquial language, fearing it would undermine their authority or affect their reputation [21, 35]. Overall, we found that readers do prefer science explanations with personal language, demonstrating that this science communication strategy on social media is helpful in engaging a broad audience. But not all readers liked or needed personal language to help them understand. As such, personal language in science communication on social media should be presented as a continuum: the effectiveness of personal language varies depending on the reader.

To help writers cater to diverse audience preferences and to accommodate writers' own hesitancy around adopting this communication strategy, we provide writers with contrasting examples of science explanations with and without personal language. Some writers' beliefs about how science communication should be was challenged when they viewed side-by-side explanations with and without personal language. By evaluating examples at both extremes, writers can more effectively discern which aspects of personal language align with their own communication style. Writers can easily evaluate which elements they wanted to keep, discard, or adapt to fit their own writing style. This process reduces cognitive load by offering writers with concrete reference points for how personal language can be used. Contrasting examples also allows writers to situate their own identities within a continuum, instead of trying to adhere to one method of communication. This contrast enables them to critically assess their own preferences, recognize effective techniques they may not have considered, and refine their approach based on the needs of their intended audience. These findings can help inform the design of AI-assisted writing tools to help writers explore a range of stylistic options, better understand audience preferences, and reflect on their own preferences.

9 LIMITATIONS AND FUTURE WORK

Our reader study only included undergraduate students in the US, and as such may not accurately reflect the general public. Additionally, we only conducted followup interviews with a subset of 8 participants which might not capture the diverse range of reader preferences. Instead, our work seeks to illuminate some reasons why readers may prefer certain strategies, and demonstrates that even within this population there are variations in reader preferences. Our dataset for science explanations only contained 15 different topics that covered 5 STEM topics (Physics, Computer Science, Civil Engineering, Psychology, and Statistics). Future work could expand the domain to life sciences and topics covered to help identify themes and trends in science communication techniques across different domains and complexities.

Our writer study only included researchers from the computer science field. Future studies should include other STEM scientists to understand how writing in different fields of study might result in different structures and style preferences. Additionally, 9 of 10 of the participants in the writer study were men which might not offer a complete

understanding of expert preferences for science communication on social media. There was little age diversity in PhD students, so additional research will need to investigate how age differences affect a scientist's comfort with using different structure and style options for science communication on social media. When using the system, writers were not asked to actually publish their final science narratives on social media. As such, writers' choices might not fully reflect how they would have written if they were to post on social media. Finally, future studies can also evaluate the longitudinal effects of using the system to evaluate whether the novelty of seeing different structures and style options wears off with prolonged usage and whether there are any long-term benefits in seeing multiple structure and style options during the drafting process for science communication.

10 CONCLUSION

It is crucial for science communication to engage the general public, and prior research suggests that using colloquial techniques from social media can be effective. Despite this, many scientists are hesitant to apply these techniques due to concerns about losing their authoritative voice. Our research highlights the complexity of public science communication and the need to balance readers' and writers' perspectives. While readers generally preferred explanations that included examples, walkthroughs, and personal language, their preferences were nuanced and context-dependent, influenced by their personal experiences and the complexity of the topic. Conversely, writers often feared that these techniques might compromise the clarity or authority of their explanations. However, when given the opportunity to explore various narrative structures and styles, writers were able to navigate their choices with greater confidence, finding a balance between colloquial and formal approaches. This suggests that effective science communication benefits from exploring diverse options, allowing writers to tailor their style to the scientific topic, their own preferences, and the needs of their audience.

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A STEM TOPICS

Computer Science:

(Introductory) Depth-First Search (Intermediate) Back Propagation (Advanced) Recurrent Neural Networks

Physics:

(Introductory) Distance and Displacement (Intermediate) Thermal Equilibrium (Advanced) Thin Film Interference

Statistics:

(Introductory) Normal Distribution (Intermediate) Central Limit Theorem (Advanced) Linear Regression

Civil Engineering:

(Introductory) Lattice Structure (Intermediate) Tensile Structure (Advanced) Curtain Wall System

Psychology:

(Introductory) Retroactive and Proactive Interference (Intermediate) Feature Integration Theory (Advanced) Walker's Action Decrement Theory

B GPT GENERATION PROMPTS

B.1 EWP

[FewShot] 6

Instructions:

Talk to a friend about the topic: [topic] in the domain: [domain]. Explain how the topic works.

Use the given example to help explain how the topic words: [example].

Use the scenario to provide additional context: [scenario].

⁶EWP-NoFewShot does not have this part.

Output format:

a piece of writing with short paragraphs (280 characters for each paragraph).

Walkthrough Guidelines:

Tell the story from a first-person perspective.

Walk through the story timeline in a sequence.

Be sure to explain each dimension of the topic in detail, relating it back to the given example and scenario.

Emotional Guidelines:

Take the second-person audience on an emotional journey.

Add visually descriptive details in the storytelling.

Use emotional languages (both negative and positive).

Add questions that echo with the audience and spark curiosity.

B.2 WP

Narrative: [Output from EWP]

Instructions:

You are given a science narrative that explains how [topic] works.

Keep the same tone and structure as the given narrative.

Remove the example of [example_label] from the narrative.

Do not include ANY examples.

Only provide a technical walkthrough of [topic] following the same structure.

B.3 EP-NoFewShot

Instructions:

Write a series of Tweets explaining the given topic: [topic] in the domain of [domain].

Make sure each Tweet is less than 280 characters.

Do not use technical jargon and define all technical components.

Do not walkthrough using timeline sequence.

Do not use words such as "before", "after", "then", "next", "also", "first", "second", "third", "last", "summary".

Explain a different technical component of the topic in each tweet in a non-sequential modular approach.

Each tweet stands alone and allows the reader to navigate through the explanations in various orders.

B.4 EW

Narrative: [Output from EWP]

Instructions:

You are given a science narrative that uses emotional and engaging language to explain a concept.

Your task is to write a new narrative that maintains the same structure of the given narrative but removes all emotional language and all subjective language.

Edit the sentences to remove 'you', 'I', and 'we' pronouns.

Do not use rhetorical or confirmation questions.

Maintain the active voice and use "people" or "student" or other general terms as the subject.

Use objective and generalizable language wherever possible.

Remove any extraneous descriptions and adjectives.

Use formal language.