Can AI tell good stories? Narrative Transportation and Persuasion with ChatGPT

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Storytelling is a human universal, but can Artificial Intelligence (AI) like ChatGPT tell a good story? Based on three pre-registered experiments, we investigated if narratives generated by ChatGPT or human lead to different levels of transportation, counterarguing, psychological reactance, self-referencing, and story-consistent attitudes, beliefs, and behaviors. Drawing on narratives examined in existing research, we crafted three narratives of comparable length and content using ChatGPT and labeled them alongside human-authored narratives as either human or AI-generated. Our findings indicate that labeling a narrative as AI-generated led to lower transportation, higher counterarguing, and lower story-consistent beliefs. However, AI-generated narratives surpassed their human-generated counterparts in reducing counterarguing and promoting story-consistent attitudes and behavioral intention, except when adapting pre-existing stories. We conclude that public skepticism towards AI persists, but language models such as ChatGPT hold the potential to outperform human writers, particularly when provided with fewer instructions.

Keywords: ChatGPT, AI, Narrative, Persuasion, Transportation, Counterarguing

Since its launch in November 2022, ChatGPT has quickly become the center of public discussion (Dwivedi et al., 2023). The language model, developed by OpenAI, interacts with users in a conversational format (OpenAI, 2022). While some characterize ChatGPT as a chatbot, it transcends the typical limitations of a chatbot, which can only answer predefined sets of questions. The language model can perform complex and unfamiliar tasks, such as summarizing texts and answering complex questions (Ouyang et al., 2022). As a generative model, ChatGPT has two unique advantages. First, unlike popular AI tools, such as image detection software, it is not limited to predefined skill sets, which makes it an Artificial General Intelligence (AGI). Second, users can interact with ChatGPT in natural language without prior training, which significantly enhanced its ease of use compared with earlier AI tools.

The high useability and ease of use of ChatGPT has prompted users to explore creative ways to unleash its power. Among them, storytelling is a novel task that has long been reserved for human creators. Indeed, narrative has long been considered an important manifest of human intelligence and culture. Societies, even in the prehistoric times, used narratives to pass along culture and knowledge, enforce social norms, and educate young generations. Narrative storytelling has also been examined in the AI context, such as storytelling robot (Striepe et al., 2021). However, such investigation has been largely limited to delivered, instead of created by AI (Messingschlager & Appel, 2022), mostly due to the power of earlier models in generating coherent storylines. With the drastic improvement in its linguistic competence, it is likely that ChatGPT may disrupt the human domination of storytelling and generate quality narratives that may entertain and educate the audience. Exploring AI-generated narratives also carries practical significance. On the one hand, research shows that narratives tailored to individual audiences' needs and wants often to achieve optimal viewing outcomes, on the other, mass-producing customized narratives require intensive human labor, which may be assisted by language models like ChatGPT. In the following sections, we review literature on language models such as ChatGPT and explore its applicability in creating engaging and persuasive narratives. We report the results of three experiments that demonstrate the potential of ChatGPT in creating narratives.

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ChatGPT and Language Models

The most recent release of ChatGPT is powered by the fourth iteration of the Generative Pre-trained Transformer (GPT-4). GPT-4 was pre-trained on an enormous amount of data collected from the Internet and finetuned through a smaller set of labeled data. The model is then adjusted according to human feedback (Ouyang et al., 2022). At its core, GPT is built on the Transformer architecture (Vaswani et al., 2017), which uses position coding and self-attention to encode and decode data, thus enabling parallel training and contextual information processing. In other words, the Transformer architecture allowed ChatGPT to scale up training set and converse with users in human languages, which hence enhances its usability and ease of use.

However, ChatGPT is not omnicompetent, and its powerful algorithm comes at an expense. In addition to concerns related to excessive energy consumption, the long and demanding training process also limits ChatGPT's ability to evolve with new information, and its "knowledge" is currently cut off at late 2021 (CITE). Another key issue is related to the factuality and creativity of content generated by ChatGPT. The language model, like most AI models, is built to *imitate* how humans write and speak based on complex probability functions. It does not necessarily *understand* what it is generating. Though the response it gives to users, in most cases, is hard to distinguish from human output, ChatGPT and most AI models are "stochastic parrots" (Bender et al., 2021), rewarded by human-sounding output but not human-like thoughts processes. Indeed, users found that ChatGPT often generates eloquent but inaccurate statements, leading to concerns about misinformation (Dwivedi et al., 2023). Relatedly, despite its ability to master complex sentence structures, ChatGPT is still best at mimicking what has been written but not creating something new. Though the best human writers often start by imitating how others write, their experience amounts to a point where they break out from the boundaries of existing knowledge and create something new. At least for now, this is unattainable for AI models like ChatGPT.

Given that the discussion on the applicability and limitations of ChatGPT and other AI models is still in its infancy, it is critical to identify and delimit their use scenarios. AI scientists and engineers have performed exceptionally well in building large and versatile models, but social scientists like us can also contribute to the transformation into a new chapter of AI-powered technologies. As an early endeavor to understand how AI may be effectively integrated into existing social systems, we argue that narrative storytelling may be a useful and testable scenario, in which we could harness the power of ChatGPT and other AI language models.

ChatGPT as a Narrative Storyteller

Defined as a sequence of events, characters, or experiences organized into a story that conveys meaning to the readers (Slater & Rouner, 2002), narrative is often considered a human universal that accompanied the evolution of societies. Even in its primitive forms, such as hunter-gatherers' communities, stories were used to foster collaboration, regulate behavior, and pass knowledge and culture to the new generations (Smith et al., 2017). The ubiquity of narrative also makes its assessment intuitive– unlike poems and other artistic forms of presentation, a person does not need much training to appreciate a good story.

The universality and intuitive appeal of narratives make them an appropriate and important use scenario for ChatGPT for a few reasons. First and foremost, the model's ability to handle complex sentences and organize them into coherent writing sets a foundation for narrative creation. Not surprisingly, stories created by ChatGPT are already circulating on platforms such as Reddit and Apple Podcast. Additionally, the limitations of ChatGPT, as illustrated above, do not prevent it from generating useful narratives. First, narrative quality is not determined by its factuality. In fact, fiction is an important genre of narratives, and research evidence shows that fictional narratives are equally persuasive and appealing as non-fictions (Braddock & Dillard, 2016). Therefore, a story generated by ChatGPT may be useful without a stringent requirement regarding factuality. Second, knowledge boundary may limit the creativity of ChatGPT, but it does not constrain the model's ability to create vivid and engaging stories. Of note, even human writers are bound by the knowledge of their time. For example, a 19th-century science fiction may feature a telephone with a screen, but a smartphone may be harder to envision. Lastly, as illustrated earlier, mass production of narratives is a needed and meaningful task. Narratives are highly effective tools in fostering social and behavioral change (Braddock & Dillard, 2016). Recent research also suggests that narratives may achieve even higher persuasiveness when customized according to the audience traits (Gray & Harrington, 2011; Liu & Yang, 2023). However, as customizing even the simplest narrative may require much human labor, ChatGPT is well-equipped to create customized narratives for various purposes at a very low cost.

Besides the utilitarian view on AI-generated narratives, it is also notable that the unique way we assess narrative quality also renders it a suitable format to evaluate and improve the performance of language models like ChatGPT. Unlike expository writings, which can often be judged based on the accuracy and comprehensiveness of information, narratives are appreciated from various perspectives, such as the vividness of characters and plots, and how captivating the story is. At the same time, despite its nuances, narrative assessment can be intuitively performed by humans without much training. It is thus possible that narratives provide a unique interface for humans to diagnose and improve AI models' creativity. In the following sections, we expand on constructs that may serve as quality indicators of AI-generated narratives, including narrative transportation, counterarguing, and story-consistent beliefs and behaviors.

Narrative Transportation

Narratives are a universal way of communicating entertaining and persuasive information to audiences. Researchers argue that one of the most potent advantages of narratives is their ability to engage the audience and transport them to an imaginary world in which their perspectives merge with the story characters (Slater & Rouner, 2002). The process of such engagement is often termed narrative transportation, which is more formally defined as a mechanism by which individuals are transported into the world of a story, losing awareness of their own physical surroundings as they become immersed in the narrative imagery and plot (Green & Brock, 2000). Research shows that narratives often induce higher levels of transportation than non-narrative messages, and transportation explains much of narratives' effects on people's attitudes, emotions, and behaviors (Braddock & Dillard, 2016). It is also notable that different narratives may induce different levels of transportation. For example, Green and Brock (2000) found that suspenseful and emotional stories tend to induce higher transportation than their less-exciting counterparts.

The scientific attention to transportation also makes it an ideal indicator of the quality of AI-generated narrative. First, it has been systematically examined with an established scale. Though no study to date has examined levels of transportation induced by ChatGPT-generated narratives, the validated measuring instruments and abundance of comparable research make it a reliable indicator of the language models' performance. Second, as transportation is related to the quality of narrative messages, assessing audience transportation offers a direct assessment of AI-generated messages. Third, transportation is related to the persuasive outcomes of narrative messages. Therefore, its assessment paves the way for subsequent analysis of AI-generated narratives' applicability in different use scenarios. Due to the lack of research evidence, we thus ask if narratives generated by ChatGPT or human differ in terms of transportation (**RQ1**)?

Cognitive Mediators of Narrative's Effects

In addition to transportation, research indicates that counterarguing, psychological reactance, and self-referencing may be subsequent cognitive processes that explain narratives' influences on readers. Counterarguing refers to disagreement with messages from the audience, which is often observed when the persuasive intent of a message is apparent (e.g., smokers counterarguing anti-smoking messages) (Slater & Rouner, 2002). However, due to narratives' ability to engage the audience in a pleasant yet unnoticeable manner, they often assume the ability to subtly shift readers' perspectives without inducing high levels of counterarguing (Moyer-Gusé & Nabi, 2010). A concept relevant to counterarguing is psychological reactance, which demarcates the feeling of being manipulated to conform to specific ideas or propositions, and explicitly persuasive messages often lead to stronger psychological reactance which results in lower compliance with message recommendations (Shen & Dillard, 2005). Similar to their effects on counterarguing, narratives were also effective in reducing reactance due to their ability to implicitly convey ideas (Moyer-Gusé & Nabi, 2010; Slater & Rouner, 2002). Research shows that narrative messages may lead to changes in health behaviors due to reduced psychological reactance (Reynolds-Tylus, 2019). Self-referencing, the process of relating one's experience with information processing (Burnkrant & Unnava, 1995), is another factor that may explain the effects of narratives. As narratives bear the potential to "transport" the audience to an imagined scenario, they also make the issues portrayed more relevant to the audience. For instance, Dunlop et al. (2010) found that a highly transporting narrative on skin cancer increased college students' self-referencing regarding skin protection.

In terms of narratives generated by ChatGPT, no research has systematically examined AI's influence on counterarguing, reactance, and self-referencing. Considering that these measures are more immediate predictors of attitudinal and behavioral outcomes as a result of narrative exposure, it is arguable that they may also serve as indicators to assess ChatGPT-generated narratives' quality. We thus propose the second set of research questions: do readers respond to narratives created by ChatGPT or humans differently in terms of counterarguing (**RQ2a**), psychological reactance (**RQ2b**), and self-referencing (**RQ2c**)?

Story-Consistent Beliefs, Attitudes, and Behaviors

As illustrated above, narratives can engage with the audience through transportation, which may lead to reduced counterarguing and psychological reactance and increased self-referencing. These underlying mechanisms all point to the effectiveness of narratives in changing audiences' beliefs, attitudes, and behaviors. Indeed, meta-analyses show that narratives often outperform other message formats in inducing these changes (Braddock & Dillard, 2016). In addition to narrative's direct effects on the outcome variables, the indirect effects of narratives through the experiential and cognitive pathways illustrated above are also worth examining. It allows us to gain a more in-depth understanding of AI-generated narratives' persuasive potential and explicate the mechanisms through which such process may take effect.

Though there is scarce evidence on language models' persuasiveness, studies show that language models such as ChatGPT may create educational vignettes in settings such as health promotion and management (Benoit, 2023; Dwivedi et al., 2023). As our goal is to examine if ChatGPT can be utilized to produce useful narratives, the attitudinal and behavioral outcomes are inevitably the most critical indicator of AI-generated narratives' quality. We thus propose the following sets of research questions. Do ChatGPT- and human-generated narratives directly lead to different story-consistent beliefs (**RQ3a**), attitudes (**RQ3b**), and behavioral intentions (**RQ3c**) in comparison to non-narrative messages? Additionally, we ask whether ChatGPT- and human-generated narratives indirectly lead to different story-consistent beliefs (**RQ4a**), attitudes (**RQ4b**), and behavioral intentions (**RQ4c**) in comparison to non-narrative messages?

Labeling Effect

Another issue critical to evaluating ChatGPT-generated narratives is that the audience may not discern a narrative created by AI from the one written by humans. Indeed, one of the major features of ChatGPT is to produce human-like content (OpenAI, 2022). In the meantime, research also shows that the general public may at least be skeptical of, if not antagonistic toward new technologies such as AI (Dwivedi et al., 2023; Ellen et al., 1991). The inability to detect AI-generated content and the general skepticism makes it essential to consider if labeling a narrative as generated by ChatGPT would change people's views and responses to it.

Existing research shows that simply labeling fiction as written by AI reduced readers' transportation, even when the fiction was all written by human (Messingschlager & Appel, 2022). Similarly, labeling a narrative video as created by AI also decreased the messages' persuasiveness, regardless of whether the video was created by AI or not (Lu & Chu, 2023). We thus propose the following hypotheses and research questions: **H1**: Labeling a narrative as created by ChatGPT will lead to lower transportation. **H2**: Labeling a narrative as created by ChatGPT will lead to higher counterarguing (a) and psychological reactance (b), and lower self-referencing (c). **H3**: Labeling a narrative as created by ChatGPT will lead to lower story-consistent beliefs (a), attitude (b), and behavioral intention (c). **RQ5**: Do AI/human labels and sources interact influence readers' response to the narratives?

The Current Study

In summary, we propose that language models such as ChatGPT may be utilized to create narratives. The use scenario is appropriate as the quality of narratives can be intuitively assessed by the readers. In the following, we report the results of three preregistered experiments assessing the quality of narratives generated by ChatGPT and human authors. All the narratives were retrieved from existing research on narratives. Study 1 featured a novel that did not have strong persuasive intent, and Studies 2 and 3 featured narratives designed to persuade. All the prompts used to create the narratives were adopted from the original narrative research.

Study 1

Method

Sample

Table 1
Sample Demographics

	Study 1	Study 2	Study 3
	M (SD) or *n (%)*	*M* (SD) or *n (%)*	*M* (SD) or *n (%)*
Age	38.43 (12.95)	41.23 (14.57)	31.77 (6.97)
Gender			
Female	135 (45.9%)	211 (48.5%)	279 (48.2%)
Male	152 (51.7%)	215 (49.4%)	290 (50.1%)
Other	7 (2.4%)	9 (2.1%)	10 (1.7%)
Race			
White or Caucasian (not Hispanic or Latino)	219 (74.5%)	311 (71.5%)	398 (68.7%)
Black or African American	17 (5.8%)	39 (9.0%)	53 (9.2%)
Hispanic or Latino	19 (6.5%)	28 (6.4%)	41 (7.1%)
Asian, Pacific Islander, or Native American	33 (11.2%)	43 (9.9%)	65 (11.2%)
Other races or ethnicities	6 (2.0%)	14 (3.2%)	22 (3.8%)
Education			
Less than High School	3 (1.0%)	2 (0.5%)	11 (1.9%)
High School / GED	30 (10.2%)	43 (9.9%)	77 (13.3%)
Some College	72 (24.5%)	87 (20%)	139 (24.0%)
2-year College Degree	30 (10.2%)	38 (8.7%)	51 (8.8%)
4-year College Degree	113 (38.4%)	180 (41.4%)	227 (39.2%)
Master's Degree	36 (12.2%)	60 (13.8%)	61 (10.5%)
Doctoral/Professional Degree	10 (3.4%)	25 (5.7%)	13 (2.2%)
Income			
Below $15,000	32 (10.9%)	40 (9.2%)	52 (9%)
$15,000 - $24,999	31 (10.5%)	40 (9.2%)	38 (6.6%)
$25,000 - $34,999	25 (8.5%)	42 (9.7%)	56 (9.7%)
$35,000 - $49,999	34 (11.6%)	55 (12.6%)	79 (13.6%)
$50,000 - $74,999	67 (22.8%)	100 (23.0%)	121 (20.9%)
$75,000 - $99,999	34 (11.6%)	61 (14.0%)	90 (15.5%)
$100,000 - $149,999	42 (14.3%)	62 (14.3%)	83 (14.3%)
$150,000 or more	28 (9.5%)	35 (8.0%)	60 (10.4%)

Upon institutional review board (IRB) approval, a sample of participants was recruited on Prolific.co in March 2023. Eligible participants reside in the United States and are fluent in English, as the experimental stimuli were written in English. In total, 322 participants provided informed consent to participate in the study. Responses from 294 participants who completed the questionnaire and passed the attention checks were retained in the subsequent analysis. The sample demographics are reported in Table 1. The preregistration at [pending copyright approval].

Stimuli and Procedures

Participants were randomly assigned to one of the four conditions. In two of the conditions, participants were informed that they will read a narrative written by ChatGPT, and in the other conditions, they were told that a famous writer wrote the story. Half of the participants read a story written by ChatGPT, and the other half read a story written by a human.

A short novel, "Two were left" by H. B. Cave, from Green and Brock (2000), was used as the human-generated narrative. We utilized this article due to its high quality and transporting potential. Additionally, as the story took place in a distant setting, our audience is unlikely to be influenced by personal experience when reading it, thus isolating the effects of narrative quality. Of note, this story does not have a strong persuasive intent, which sets a baseline for the next two studies investigating ChatGPT-generated persuasive narratives. Correspondingly, we did not measure psychological reactance and self-referencing as the persuasive intent of the experimental narratives was not salient. The AI-generated version of the story was created using the story's description in Green and Brock (2000). We asked ChatGPT to create a narrative of a similar length to the human version (i.e., 480 words). The prompt we used to create the narrative and the stimuli messages are available at [pending copyright approval].

Measurement

The 11-item transportation measure was adapted from Green and Brock (2000). Meta-analyses show that the scale is a reliable indicator of audience engagement with narratives. Sample items include “The story affected me emotionally”. Participants responded to the items on a five-point scale (1 “Strongly disagree” to 5 “Strongly agree; Alpha = 0.81). Counterarguing was measured with a four-item scale adopted from Moyer-Gusé and Nabi (2010). Sample items include “I found myself looking for flaws in the way information was presented in the story”. Responses are anchored on a five-point scale (1 “Strongly disagree to 5 “Strongly agree”). Notably, the reliability of this scale was low (alpha = 0.63), possibly due to the inclusion of two reverse-coded items. We addressed this issue in Study 2. Similar to Green and Brock (2000), we measured participants’ story-consist beliefs with three items such as “A starving person may betray friends in order to obtain food”. However, responses to the reverse-worded question did not correlate well with the other two variables ($r_1 = 0.21$, $p < .001$; $r_2 = 0.09$, $p = 0.29$), which correlated better with one another ($r = 0.34$, $p < 0.001$). We thus only retained the means of the other two items as the outcome variable. We also asked participants to report attitudes towards the main character and his dog, with two sets of three semantic differentials (e.g., 1 “Bad” to 5 “Good”). The scales were reliable (alpha = 0.79 for the boy, alpha = 0.76 for the dog).

Result

Figure 1 shows the condition-wise distribution of all the outcome variables, and Table 2 shows the results of the ANOVA models. In response to **RQ1** and **H1**, two sets of two-way ANOVAs were conducted. Source labels, actual sources, or their interaction did not lead to a significant difference in transportation. However, a closer look at the borderline significant effects on transportation shows that the human-created narrative led to higher transportation than the ChatGPT-generated narrative when they were both labeled as human-authored. However, the direction of such effects reversed when the narratives were labeled as AI-generated. In response to **RQ2** and **H2**, a similar ANOVA was performed with counterarguing as the dependent variable. Results show a significant difference between source labels and the actual source, but no significant interaction exists between these factors. Participants generated more counterarguing when the source was attributed to AI, but their actual counterarguing was higher when reading a human-author narrative than the one generated by ChatGPT. In response to **RQ3** and **H3**, three additional ANOVAs were employed. Results showed that the source or label of the narrative did not have any significant main or interaction effect. However, there were significant main effects of narrative source and label for attitudes toward Noni, the main character in the story, and his dog. Participants liked the characters more in the human-labeled stories, but they also liked the characters more in the ChatGPT-generated narratives.

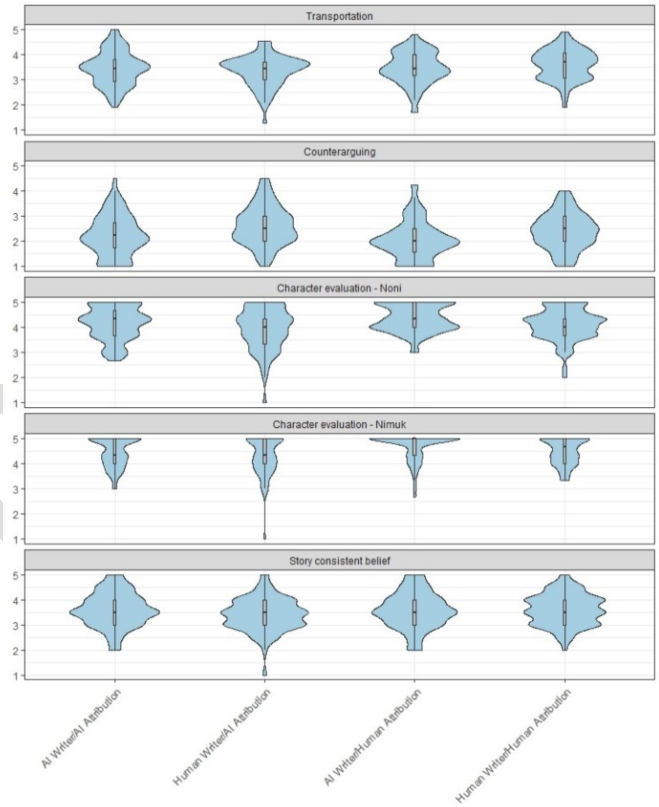

Figure 1. *Distribution of key outcome variables in Study 1*

Discussion

Participants reacted differently to narratives labeled as human or ChatGPT-authored. Overall, they were more transported and less likely to formulate counterarguing when the narratives were attributed to a human author. They also liked the characters more in the seemingly human-authored narratives. Such finding is consistent with existing research (Lu & Chu, 2023). More interesting is that the readers were less likely to counterargue the narratives generated by ChatGPT and liked the AI-generated characters more. The discrepancy between reader responses to narratives created by or attributed to a human and AI is worth exploring. On the one hand, it shows that ChatGPT may create engaging narratives, but on the other, people may still be skeptical about its use in creating stories.

Study 2

Study 1 demonstrates an initial assessment of AI-generated narratives. We are also interested in whether ChatGPT would succeed in creating narratives designed to persuade, especially in comparison to non-narrative messages. Study 2 addresses this goal by replicating Niederdeppe et al. (2011), which investigated narratives' effects on people's individual and social attribution of responsibility associated with obesity. As the research shows, narratives were successful in helping readers identify the social cause of obesity and promoting policies addressing the health issue (Niederdeppe et al., 2011).

Method

Sample

Participants were recruited from Prolific panels in March 2023. Because Niederdeppe et al. (2011) found that their narratives only led to significant attitudinal shifts in people who identified as liberal Democrats, the corresponding partisanship and ideological filters were employed when recruiting participants. We targeted participants residing in the U.S. and fluent in English. 442 Respondents opened the link, and 435 passed all attention checks (Table 1).

Stimuli and Procedures

Following a similar procedure in Study 1, participants were randomly assigned to one of the four narrative conditions and a non-narrative condition. The narrative message from Niederdeppe et al. (2011) was adapted from a longer story about a young person living in Philadelphia who strived to overcome health issues related to obesity. To ensure consistency between the narratives, we instructed ChatGPT to create a new narrative based on the original story (RWJF, 2008) and the stimuli description in Niederdeppe et al. (2011). As the original study's description also addresses the persuasive intent of the message (Niederdeppe et al., 2011), we asked ChatGPT to implicitly convey such information to ensure that the messages are comparable. The non-narrative message from the study was used as a control ([pending copyright approval]). Like study 1, we assigned different labels to the narrative messages. In the human-labeled narrative and non-narrative conditions, the story was attributed to a team of researchers, and in the AI-labeled conditions, the story was attributed to "ChatGPT, a powerful AI language model".

Measurement

Transportation was measured with the same scale in Study 1 (alpha = 0.84). We adjusted the reverse-worded items in the counterarguing scale, so all items are in the same direction. The edited scale was reliable (alpha = 0.90). Psychological reactance was measured on a four-item scale (Shen & Dillard, 2005). Sample items include "The message threatened my freedom to choose". Participants rated their agreement with these statements on a five-point scale (1 "Strongly disagree" to 5 "Strongly agree"). The scale achieved satisfactory reliability (alpha = 0.78). Self-referencing was measured on a four-item scale with items such as "to what extent did you think the message is related to you personally?" (Dunlop et al., 2010). Responses to the scale were recorded on a five-point scale (1 "Not at all" to 5 "A great deal"; alpha = 0.88).

Following Niederdeppe et al. (2011), we measured responsibility attribution of the cause and solution of obesity in the U.S. For cause attribution, participants were asked to indicate how much four social causes, such as "healthy food is too expensive for many people" (alpha = 0.66), and four individual causes, such as "most people lack the willpower to diet regularly" (alpha = 0.84) are responsible for causing obesity on a five-point scale (1 "Not at all" to 5 "A great deal"). For solution attribution, participants rated if individuals (single-item measure) and external factors such as "manufacturers of unhealthy foods" (alpha = 0.84) bear the responsibility of solving the obesity issue on the same five-point scale. We measured participants' support of seven policies addressing obesity (e.g., "Require restaurants to list the calorie count on their menus") on a five-point scale (1 "Strongly oppose" to 5 "Strongly support"; alpha = 0.78).

Results

Figure 2 reports the condition-wise distribution of the outcome variables. We first inspected if narrative sources and labels influenced transportation (**RQ1** and **H1**; Table 2). Results indicate that the human-generated narrative outperformed the AI-generated narrative, but the source label or interaction term had no significant effect. Similarly, we found that the human-authored narrative led to higher levels of self-referencing than the AI-generated story, but such an effect was not significant for narrative labels or the interaction term.

Table 3
Results of the two-way ANOVA models examining message source and label's effects on the outcome variables

	Message Source				Message Label				Message Source × Message Label	
	Human	AI	*F*	Partial η^2	Human	AI	*F*	Partial η^2	*F*	Partial η^2
Study 1										
	M (SD)	*M (SD)*	*F* (1,290)	Partial η^2	*M (SD)*	*M (SD)*	*F* (1,290)	Partial η^2	F (1,290)	Partial η^2
Transportation	3.49 (0.62)	3.47 (0.66)	0.08	0.000	3.54 (0.63)	3.41 (0.65)	3.34	0.011	2.88	0.010
Counterarguing	2.52 (0.77)	2.17 (0.79)	15.57	0.051	2.24 (0.76)	2.44 (0.82)	4.79*	0.016	0.06	0.000
Story-Consistent Beliefs	3.51 (0.66)	3.59 (0.72)	0.96	0.003	3.59 (0.68)	3.51 (0.69)	1.10	0.004	1.87	0.006
Attitudes towards character (Noni)	4.00 (0.74)	4.24 (0.61)	9.15**	0.031	4.22 (0.59)	4.03 (0.76)	5.27*	0.018	0.02	0.000
Attitudes towards character (Nimuk)	4.38 (0.65)	4.56 (0.57)	6.64*	0.022	4.57 (0.54)	4.38 (0.67)	7.48**	0.025	0.24	0.001
Study 2										
	M (SD)	*M (SD)*	*F* (1,343)	Partial η^2	*M (SD)*	*M (SD)*	*F* (1,343)	Partial η^2	F (1,343)	Partial η^2
Transportation	3.6 (0.64)	3.32 (0.78)	13.42	0.038	3.52 (0.71)	3.42 (0.74)	1.91	0.006	0.55	0.002
Counterarguing	1.69 (0.85)	1.84 (0.99)	2.44	0.007	1.72 (0.94)	1.81 (0.91)	0.79	0.002	3.13	0.009
Psychological Reactance	1.62 (0.7)	1.62 (0.76)	0.00	0.000	1.62 (0.73)	1.63 (0.73)	0.01	0.000	0.34	0.001
Self-Referencing	3.61 (1.03)	3.26 (1.15)	9.12**	0.026	3.52 (1.08)	3.37 (1.12)	1.76	0.005	0.27	0.001
Attribution - Social Cause	3.99 (0.72)	3.97 (0.8)	0.09	0.000	4.04 (0.72)	3.92 (0.8)	2.05	0.006	0.52	0.001
Attribution - Individual Cause	3.19 (0.92)	3.12 (0.99)	0.43	0.001	3.11 (0.96)	3.21 (0.95)	0.88	0.003	1.08	0.003
Attribution - Social Solution	4.21 (0.86)	3.98 (1.07)	5.25*	0.015	4.11 (1)	4.09 (0.95)	0.04	0.000	0.04	0.000
Attribution - Individual Solution	3.02 (0.87)	2.97 (0.88)	0.3	0.001	2.96 (0.9)	3.03 (0.85)	0.48	0.001	0.2	0.001
Policy Support	4.21 (0.51)	4.17 (0.62)	0.34	0.001	4.22 (0.53)	4.16 (0.6)	0.91	0.003	0.09	0.000
Study 3										
	M (SD)	*M (SD)*	*F* (1,381)	Partial η^2	*M (SD)*	*M (SD)*	*F* (1,381)	Partial η^2	F (1,381)	Partial η^2
Transportation	3.36 (0.79)	3.35 (0.74)	0.01	0.000	3.48 (0.7)	3.23 (0.8)	10.47**	0.027	0.76	0.002
Counterarguing	1.88 (1.03)	1.66 (0.77)	5.8*	0.015	1.62 (0.8)	1.91 (1)	9.50**	0.024	0.04	0.000
Psychological Reactance	2.31 (0.80)	2.28 (0.72)	0.11	0.000	2.36 (0.76)	2.23 (0.76)	2.74	0.007	0.43	0.001
Self-Referencing	3.39 (1.01)	3.32 (1.02)	0.4	0.001	3.43 (1)	3.28 (1.02)	2.07	0.005	1.18	0.003
Perceived Susceptibility	3.46 (0.78)	3.48 (0.78)	0.02	0.000	3.51 (0.83)	3.43 (0.73)	0.89	0.002	0.00	0.000
Perceived Severity	4.33 (0.75)	4.34 (0.68)	0.03	0.000	4.4 (0.66)	4.28 (0.76)	3.04	0.008	0.14	0.000
Attitudes toward Skin Protection	4.55 (0.59)	4.62 (0.56)	1.81	0.005	4.64 (0.53)	4.53 (0.61)	3.00	0.008	0.06	0.000
Behavioral Intention	3.88 (0.81)	3.85 (0.87)	0.07	0.000	3.94 (0.85)	3.79 (0.82)	2.89	0.008	0.02	0.000

Note. * $p < .05$; ** $p < .01$; *** $p < .001$

There was no significant difference between narrative source, label, or their interaction in counterarguing and psychological reactance (**RQ2** and **H2**). The only significant effects on the outcome variables (i.e., responsibility attribution and policy support) were the narrative sources' impacts on individual solution attribution, as participants were less likely to attribute the responsibility to individuals (**RQ3** and **H3**). Responding to **RQ4**, we ran additional one-way ANOVAs, including the non-narrative group. Significant effects were identified on transportation (F (4,428) = 4.77, $p < .001$, $\eta^2 = 0.043$), counterarguing (F (4,428) = 2.71, $p < .05$, $\eta^2 = 0.024$), psychological reactance (F (4,428) = 4.11, $p < .01$, $\eta^2 = 0.037$), and self-referencing (F (4,428) = 3.26, $p < .05$, $\eta^2 = 0.030$). However, no significant effects were observed on the responsibility attribution variables and policy support. Post-hoc analyses were conducted to inspect the condition-wise differences with Bonferroni adjustment (Figure 2). Observably, human-author/human-label condition outperformed the AI-author/AI-label and the non-narrative condition in transportation and psychological reactance. The human-author/human-label narrative also led to higher transportation than the AI-author/human-label narrative and lower counterarguing than the non-narrative condition. However, it is notable that all narrative conditions, regardless of label and source, led to lower psychological reactance than the non-narrative condition.

We utilized the PROCESS Macro in SPSS (Hayes, 2017) to explicate the indirect effects of the messages. The dummy-coded condition variable with the non-narrative condition as the reference group was modeled as the independent variable. Transportation was entered as the immediate mediator of message effects. Counterarguing, psychological reactance, and self-referencing were modeled as subsequent parallel mediators. Responsibility attributions and policy support were used as the outcome variables. Observably, two human-authored narratives led to higher levels of social cause attribution through the mediation of transportation and self-referencing (B = 0.028 for human-author/AI-label, B = 0.051 for human-author/human-label). All narrative conditions led to lower individual cause attribution and higher policy support via the mediation of psychological reactance (B ranges from -0.057 to -0.049 for cause attribution; B ranges from 0.037 to 0.043 for policy support). The human-author/human-label messages led to higher individual solution attribution (B = 0.062) and higher policy support (B = 0.035) than the non-narrative message via the mediation of counterarguing.

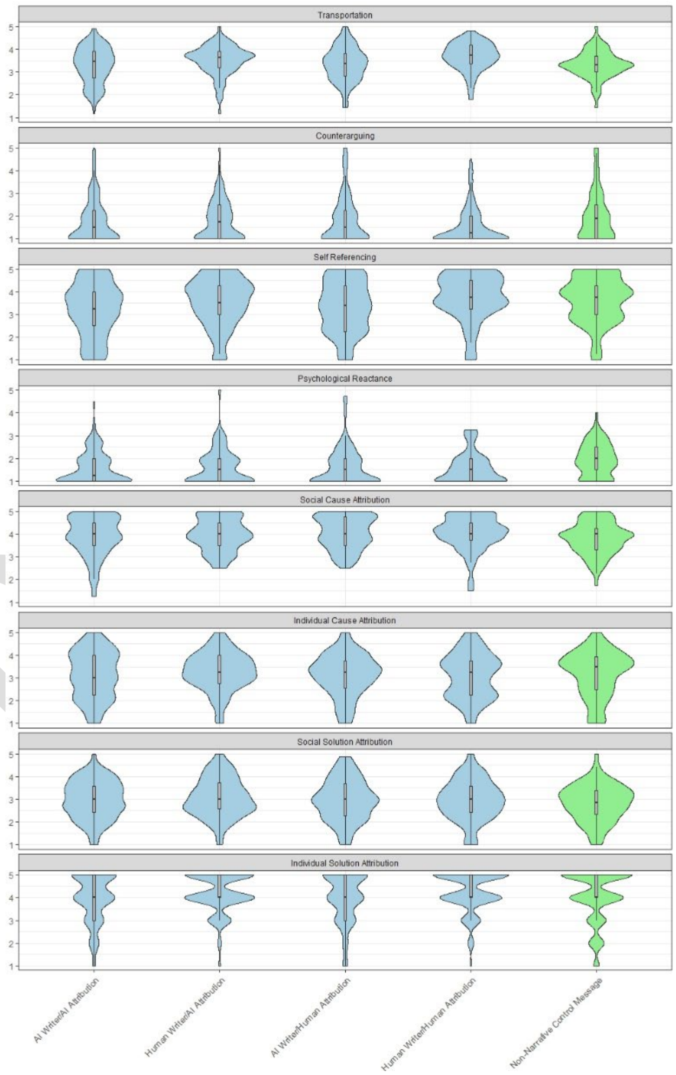

Figure 2. *Distribution of key variables in Study 2*

Discussion

The human-authored narrative outperformed the ChatGPT-generated narrative in engaging the participants and reducing resistance to the embedded persuasive content. As a result, the human-generated narrative also led to better persuasive outcomes. However, it is also notable that the ChatGPT-generated narrative led to lower psychological reactance than the non-narrative condition, which mediated some of its persuasive effects on the outcome variables. Multiple reasons may have led to ChatGPT's underperformance. First, the prompt utilized to generate the story was much longer than the one used in Study 1, as it asks for an adaptation of an existing story. Second, the story created by Niederdeppe et al. (2011) used more paragraphs than the one created by ChatGPT (which seems to be a common issue for the language model). The smaller pieces of text may be more digestible than the long paragraphs.

Study 3

Study 3 further examines ChatGPT's potential in generating persuasive narratives, which compared shorter AI and human-created narratives. We replicated Dunlop et al. (2010), which examined if narratives effectively promoted skin protection. This issue was selected for two reasons. First, just like obesity, skin protection and skin cancer prevention are directly related to people's lives, ensuring our experiments' comparability. Second, the focus on skin protection allows us to test ChatGPT's potential to generate narratives that motivate personal behavioral change. Study 3 also employed a larger sample than the first two studies.

Method

Sample

In March 2023, a sample of 579 participants was recruited on Prolific.co (Table 1). Like the first two studies, we recruited participants residing in the U.S. and fluent in English. As the stimuli from Dunlop et al. (2010) were geared toward the risks of skin cancer among young people aged between 18 and 44, we applied the same age filter in sampling. 605 People signed up for the study, and 28 were dropped due to incompletion or failed attention checks.

Stimuli and Procedures

Similar to Studies 1 and 2, participants were randomly assigned to one of six conditions, including four experimental conditions, one non-narrative control and one no-message control condition. Participants only rated their risk perception, attitudes, and behavioral intention in the no-message control condition. Before reading the message, participants in the other conditions were informed that they would read a message created by an advertising agency or ChatGPT, depending on the label manipulation. We modified Dunlop et al.'s (2010, Study 2) narrative and non-narrative messages, as they were written in the Australian context. We instructed ChatGPT to create a narrative of similar length using the descriptions in Dunlop et al. (2010). See [pending copyright approval] for the stimuli messages.

Measurement

Transportation (alpha = 0.87), counterarguing (alpha = 0.91), reactance (alpha = 0.74), and self-referencing (alpha = 0.88) were measured with the same scales from Study 2. Perceived risk of skin cancer was measured with two sets of questions examining perceived susceptibility (e.g., "I am at risk of getting skin cancer") and severity (e.g., "I believe that skin cancer is extremely harmful") of skin cancer (Chu & Liu, 2021). Responses were recorded on a five-point scale (1 "Strongly disagree" to 5 "Strongly agree"), and the scales were reliable (alpha = 0.82 and 0.89). Attitudes toward skin protection were measured with seven semantic differential items (e.g., 1 "bad" to 5 "good") from Dunlop et al. (2010). The scale was reliable (alpha = 0.94). Intention to adopt skin protection was measured with four items, such as "I intend to change my skin protection behavior" with a five-point scale (1 "Strongly disagree" to 5 "Strongly agree"). The scale also achieved satisfactory reliability (alpha = 0.85).

Results

Two-way ANOVAs were employed in response to **RQ1**-**RQ3** and **H1**-**H3** (Table 2 and Figure 3). Results of the models indicate that attributing a narrative to human authors led to higher transportation and lower counterarguing, partially supporting **H1** and **H2**. The human-labeled narratives also outperformed their AI-labeled counterparts in instigating higher severity perception, more positive attitudes, and stronger behavioral intention, which supported **H3**. Differently, AI and human-authored narratives did not differ significantly on most variables. However, the ChatGPT-generated narrative achieved lower counterarguing than the human-authored story, regardless of source label. No significant interaction was identified (**RQ5**).

We ran additional one-way ANOVAs among the five message conditions to examine whether AI and human-generated narratives led to different message effects than non-narrative ones. Significant effects were identified for transportation (F (4,475) = 2.83, p < 0.05, η^2 = 0.023), counterarguing (F (4,475) = 4.18, p < 0.01, η^2 = 0.034), and self-referencing (F (4,475) = 2.57, p < 0.05, η^2 = 0.021). Post-hoc analysis showed that the human-author/AI-label condition led to lower transportation than the human-author/human-label condition ($p_{adjusted}$ < 0.05), aligning with the labeling effects identified earlier. Additionally, we found that the human-author/AI-label condition led to higher

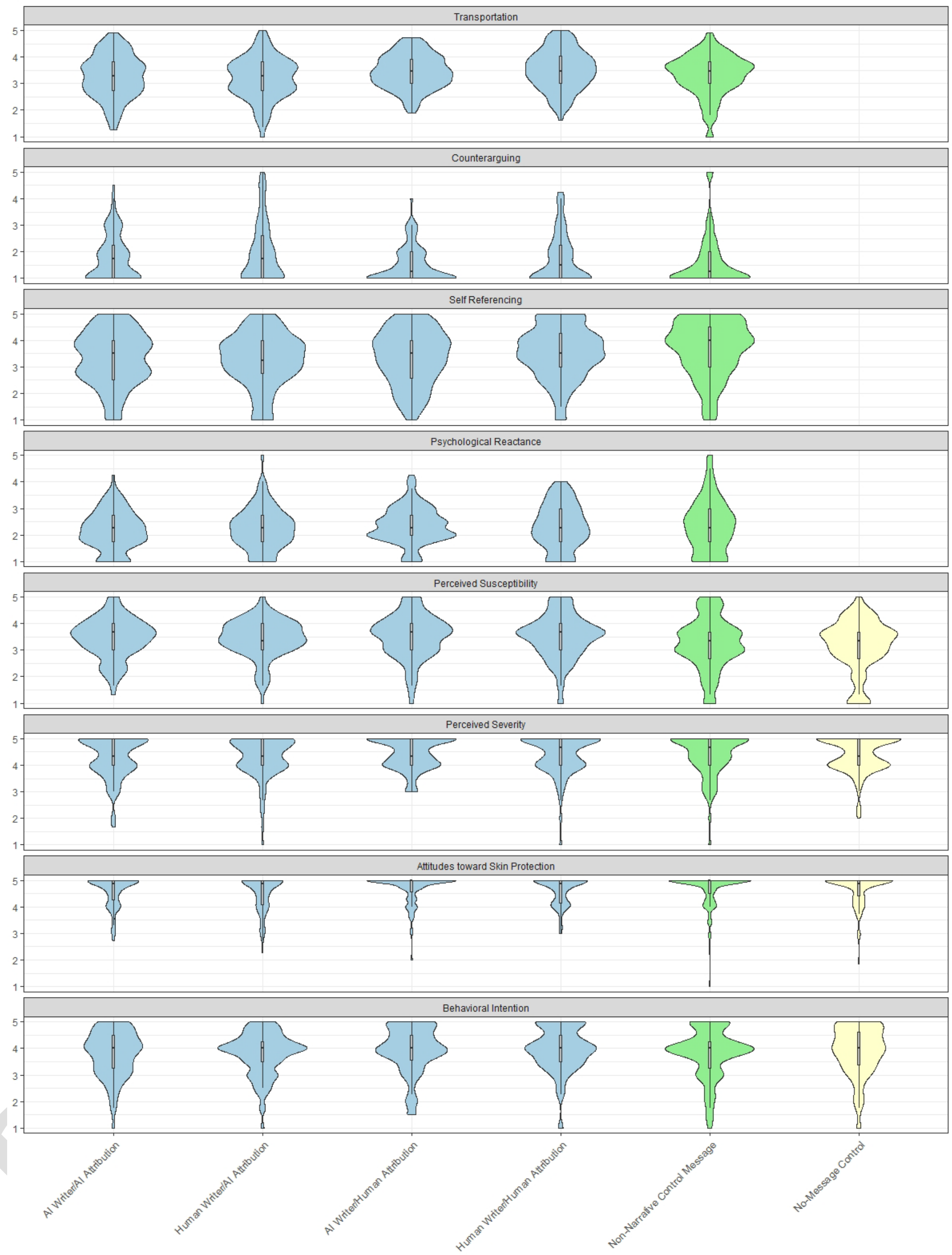

Figure 3. *Distribution of key variables in Study 3*

counterarguing than both the AI-author/human-label and the non-narrative conditions. No significant condition-wise differences were identified for self-referencing after applying the Bonferroni adjustments (**RQ3**).

We did not find any significant difference between-condition difference in the attitudinal or behavioral outcomes (**RQ4**). We ran additional mediation models to examine the indirect message effects. Quite surprisingly, the non-narrative condition led to higher risk perception, positive attitudes, and behavioral intention than all narrative messages through self-referencing mediation (*B* ranges from -0.18 to -0.04). In addition, the human-author/AI-label narrative messages led to lower severity perception, positive attitudes, and behavioral intention than the non-narrative message via the mediation of counterarguing (*B* ranges from -0.08 to -.06).

Lastly, we ran four one-way ANOVAs to examine if the message conditions led to a significant difference in the outcome variables compared to the no-message control. Results indicate that significant differences exist in participants' susceptibility perception (F (5, 572) = 2.67, $p < 0.05$, $\eta^2 = 0.023$). Post-hoc tests did not show any significant pairwise differences. However, the difference in susceptibility perception between the AI-author/human-label narrative condition and the no-message control were approaching statistical significance ($p = 0.08$), where the former led to higher perceived susceptibility (mean difference = 0.34).

Discussion

The findings largely replicated what we found in Study 1. Labeling a narrative written by ChatGPT decreased transportation and increased counterarguing than when the narrative was attributed to humans. However, the story generated by AI received less counterarguing than the one written by human researchers. Additionally, we found that the story attributed to ChatGPT but written by human authors consistently underperformed than other messages, but the ChatGPT-authored/human-label generated more positive outcomes. Thus, it is reasonable to suggest that the public may be skeptical about content generated by AI, but they were more receptive to AI-generated messages. It was unexpected that we did not replicate Dunlop et al. (2010), who found that the narrative messages outperformed the non-narrative messages in inducing attitudinal and behavioral change. One possible reason may be the shorter length of the non-narrative message and its point-list format. Nevertheless, the underwhelming indirect effects were observed in all narrative conditions, particularly for the human-authored/AI-label condition, which does not negate the comparative advantage of AI-generated narratives over the human-authored ones.

Meta-Analysis

The consistency of measures among the three studies allowed us to examine the combined effects of message source and label. Pooling responses from the narrative conditions across the three studies, we conducted a meta-analysis of message effects with a combined sample has 1,028 participants. ANOVA results indicate that message label led to significant differences in transportation (F (1,1024) = 14.10, $p <$ 0.001, $\eta^2 = 0.013$) and counterarguing (F (1,1024) = 11.18, $p < 0.001$, $\eta^2 = 0.011$). The source of the message also led to significant differences in transportation (F(1,1024 = 5.52, $p < 0.05$, $\eta^2 = 0.005$) and counterarguing (F(1,1024) = 4.91, $p < 0.05$, $\eta^2 =$ 0.005). Labeling a narrative as ChatGPT-authored led to lower transportation and higher counterarguing than a message attributed to humans. ChatGPT-generated narratives, in general, also led to lower transportation than human-created narratives, but it generated lower counterarguing than the human-authored ones.

General Discussion

The rapid development of AI has brought us into uncharted territory, where the boundary of AI's ability is still unknown. The three experiments reported here provide an initial outlook of large language models, such as ChatGPT's ability to create engaging and persuasive narrative stories. It may be reassuring for some that the model did not consistently outperform human writers. However, in Study 1 and Study 3, readers were less likely to counterargue narratives created by ChatGPT than ones written by a novelist or researchers. However, in Study 2, we found that the human adaptation of a longer story was more engaging and persuasive than the version created by ChatGPT. One possible reason for such a discrepancy may be the prompts used to generate the narratives. Specifically, the increase in parameters (i.e., longer instructions) may have limited ChatGPT's ability to create an "original" narrative, as it instead focused on retaining most of the information from the original text. Differently, the researcher's version was created to enhance the story's persuasiveness instead of the fidelity to the original text, giving them more flexibility when incorporating content from the longer story. Similarly, the better performance of ChatGPT in Studies 1 and 3 may be related to the shorter prompts.

One question we may thus ask is why the shorter narratives created by ChatGPT were more effective in reducing counterarguing and promoting story-consistent beliefs. A closer look at the texts may provide some clues. For example, in Study 1, the original story used smaller paragraphs and a more dynamic presentation of the character's internal struggle. Differently, the version created by ChatGPT was less vibrant, and the story was delivered in a somewhat monotonous voice. Similarly, in Study 3, the AI-generated narrative also involved a less dramatic presentation of the character's ordeal (e.g., "the surgery to remove the melanoma left a scar on my chest" versus "after the surgery, I woke to see a huge gash in my chest" by ChatGPT). However, as one may reasonably ask, wouldn't the less dynamic language of ChatGPT lead to decreased engagement and persuasiveness instead of better performances? We argue that this may not necessarily be the case. Specifically, as ChatGPT was trained with the enormous amount of textual data generated by human beings, it is a likely tendency for the model to generate output that resembles the most common way of expression. The commonness of expression, though on the one hand, led to less vibrant language styles, may on the other hand, be easier to comprehend and access. Such a possibility is similar to the beauty-in-averageness effects observed in research on physical appearance, where beauty often results from averaging the characteristics of people (Rubenstein et al., 2002). In the context of narrative generation, it is also possible that AI models like ChatGPT may generate "good" narratives, but they may still lack the ability to write an exciting and creative story.

Unlike the mixed findings related to ChatGPT's ability to create engaging and persuasive narratives, one common theme observed in the three studies is the clear dislike of stories labeled as AI-generated. Participants rated the narratives as less engaging and were more likely to resist the content of the narratives when they were attributed to the language model, even when they were, in fact, written by human authors. Such finding is consistent with existing research (Lu & Chu, 2023; Messingschlager & Appel, 2022). Resistance to new technologies is never new, and what we now consider an integral part of modern lives was often not welcomed when first invented (Ellen et al., 1991). However, AI's disruptive impacts and complexity pose more uncertainty than many technologies, which is further exacerbated by the fact that many of the underlying mechanisms of AI models were not even transparent to the experts developing them. Such uncertainty has led to much frustration, evident in the recent open letter signed by experts in the field calling for a pause of large AI experiments. The development and application of AI requires knowledge of the models and how to integrate them with existing social structures effectively. Findings from the current study once again highlight the importance of public perception and opinion when implementing AI-powered technologies.

Lastly, this study also has limitations. First, though we examined three ChatGPT-generated narratives, caution is still needed when generalizing the findings to a wider context. The versatility of language models such as ChatGPT allows them to create diverse content when the prompts are modified. We thus recommend future research to examine the performance of AI-generated narratives using different instructions. Second, we only examined the quality of textual content created by an AI model. Other generative models may produce audio and visual content of different quality. It is thus important to replicate the experiments with other AI models. Lastly, all research participants were sampled on online panels, which may limit the generalizability of our conclusions. Compared with the general population, these participants may be more receptive to new technologies such as AI. In the meantime, considering that even this group showed some levels resistance to content labeled as AI-generated content, the general public opinions on AI may be even more skeptical. Nevertheless, we recommend research to further examine public perceptions of AI models like ChatGPT.

Conclusion

In conclusion, this manuscript comprehensively investigates the quality of AI-generated narratives. We found that while AI-generated narratives may not consistently match human-authored content, readers display lower resistance toward them. As language models like ChatGPT continue to evolve, their ability to create compelling narratives will likely improve, further highlighting the importance of evaluating narrative quality as a performance metric for generative models. Moreover, this study underscores the significance of interdisciplinary collaboration between social science and AI research. By examining the human aspects of AI-generated content, we contribute valuable insights that inform the development and application of AI technologies. By fostering a better understanding of the interaction between humans and AI, we can help shape a future where AI systems are more advanced and more in tune with their users' needs, expectations, and preferences. Ultimately, this research paves the way for further exploration of the social implications of AI-generated narratives and their potential impact on society.

Data Availability Statement

The data underlying this article will be shared on reasonable request to the corresponding author.

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