

# Towards Effective Counter-Responses: Aligning Human Preferences with Strategies to Combat Online Trolling

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## Abstract

Trolling in online communities typically involves disruptive behaviors such as provoking anger and manipulating discussions, leading to a polarized atmosphere and emotional distress. Robust moderation is essential for mitigating these negative impacts and maintaining a healthy and constructive community atmosphere. However, effectively addressing trolls is difficult because their behaviors vary widely and require different response strategies (RSs) to counter them. This diversity makes it challenging to choose an appropriate RS for each specific situation. To address this challenge, our research investigates whether humans have preferred strategies tailored to different types of trolling behaviors. Our findings reveal a correlation between the types of trolling encountered and the preferred RS. In this paper, we introduce a methodology that recommends an appropriate RS for various trolling behaviors. This approach is supported by a dataset we constructed, which aligns these strategies with user preferences. This enables the generation of effective counter-responses by recommending the most appropriate strategies based on these preferences. The experimental results demonstrate that our proposed approach improves discussion quality and reduces the negative effects of trolls, thereby enhancing the online community environment.

## 1 Introduction

In online communities, trolling is characterized as a disruptive activity, such as teasing, provoking anger, offending others, dominating discussions, or manipulating opinions (Mihaylov and Nakov, 2016; Golf-Papez and Veer, 2017). Such behaviors often interfere with the productive exchange of ideas (Bishop, 2013), contribute to polarized and hostile atmospheres (Craker and March, 2016), and cause significant emotional distress to victims (Carmacho et al., 2018). To preserve a positive community atmosphere, moderation is essential, as it

helps mitigate the impact of trolling and maintain the continuity of constructive discussions (Wise et al., 2006; Kraut and Resnick, 2012).

However, determining the appropriate response to trolls is not straightforward. As Hardaker (2010) noted, the range of troll behaviors is diverse, and the corresponding response strategies for addressing them should vary accordingly. For example, when faced with highly politicized and offensive comments, the responses should explicitly and strongly incorporate clear warnings. By contrast, when a troll shares off-topic opinions during focused discussions, the responses should gently guide them to realign their contributions with the goals of the discussion. This range of behaviors and required responses adds to the challenge of choosing the most appropriate strategy for a given situation.

A recent study (Mun et al., 2023) has found that humans tend to prefer certain strategies when countering hate speech. Inspired by this finding, we clearly speculated that humans might also have a preferred response tailored to each distinct troll situation. To investigate this, we explored whether preferences exist for various response strategies to different trolling behaviors. Our findings showed a clear correlation between the types of trolling encountered and response strategies preferred, enhancing our understanding of how to counter different trolling behaviors appropriately.

In this paper, we aim to develop a method for generating the most effective strategy for responding to trolls in diverse situations, thereby promoting a desirable online community environment. Accordingly, we propose a method that recommends a specific response strategy for each type of trolling behavior, which enables the generation of appropriate Counter-Responses (CR) to trolls aligned with human preference. To this end, we investigated the relationship between different Trolling Strategies (TS) and the corresponding preferred

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084	<b>Response Strategies (RS).</b> Then, we constructed a	criticized for potential contagion of such behav-	134
085	dataset that matches RS to user preferences across	ior (Cheng et al., 2017), leading to censorship accu-	135
086	various troll contexts. Utilizing this dataset, we	sations (Richards and Calvert, 2000), and neglect-	136
087	developed a recommendation system for RS and	ing user feedback (Myers West, 2018). Addition-	137
088	designed a CR generation methodology that se-	ally, Zheng et al. (2023) found that the commonly	138
089	lects the most appropriate strategy based on this	used gentle guiding approach is not universally pre-	139
090	system. Our experimental results demonstrate that	ferred. In this paper, we explore how to choose	140
091	our methodology effectively promotes constructive	the appropriate RS for countering trolls, motivated	141
092	discussions and reduces the negative impacts of	by the previous research that highlights significant	142
093	trolling, as well as improving the engagement of	variations in preferences for responding to hate	143
094	community users.	speech (Mun et al., 2023).	144
095	Our contributions and findings are threefold:		
096	• This is the first study to explore the relationship	<b>3 Methodology</b>	145
097	between human preferences and response strate-	In this section, we explore the relationship between	146
098	gies for addressing various trolling behaviors,	TS and preferred RS, detailing the process we used	147
099	shedding light on novel approaches for managing	to construct a dataset that aligns human preferences	148
100	online communities.	with RS. Furthermore, we outline our method for	149
101	• We propose a novel CR generation methodology,	generating CRs using this dataset.	150
102	aligning user preferences with response strate-		
103	gies, and enhancing the effectiveness of auto-	<b>3.1 Data Collection</b>	151
104	matic moderation.	Our data collection involves crawling posts and	152
105	• Our experimental results demonstrate that our	troll comments from various subreddits on Reddit	153
106	proposed approach guides constructive discus-	published in 2022. To ensure that collected posts	154
107	sion and mitigates the negative impacts of trolls.	and comments provide adequate contextual infor-	155
		mation for understanding discussions, we applied	156
108	<b>2 Related Works</b>	a character limit of a minimum of 12 and a maxi-	157
		mum of 512 characters. We excluded texts deleted	158
109	Troll behaviors vary widely, from explicit expres-	by Reddit or users and samples containing external	159
110	sions of hate, such as promoting discrimination	links or media materials to prevent loss of contex-	160
111	based on gender, to subtle annoyance, including di-	tual information due to embedded links, photos, or	161
112	gressing onto irrelevant topics or misleading others	videos. To gather texts with a high likelihood of	162
113	with harmful advice (Herring et al., 2002; Hardaker,	being troll comments, we first selected posts that	163
114	2010; Fichman and Sanfilippo, 2016; Mihaylov	had root comments with negative scores. We then	164
115	and Nakov, 2016; Bratu, 2017; Golf-Papez and	employed GPT-3.5 for troll classification. Further	165
116	Veer, 2017). Hardaker (2013) outlined the types of	details are shown in Appendix A.2.	166
117	trolling strategies ranging from covert to overt and		
118	examined the types of response strategies accord-	<b>3.2 Investigation of Human Preference</b>	167
119	ingly. Attempts to implement automatic counter-	We adopted the taxonomy of trolling behavior de-	168
120	trolling have been made (Chung et al., 2021; Zhu	veloped by Hardaker (2013), which classifies TS	169
121	and Bhat, 2021; Lee et al., 2022; Gupta et al., 2023;	ranging from covert to overt. This taxonomy classi-	170
122	Furman et al., 2023; Yu et al., 2023), but the chal-	fies trolling behaviors along a continuum, starting	171
123	lenge of automatically selecting the appropriate RS	from the covert strategy, such as <i>Disgression</i> , to	172
124	still remains. In this study, we explore effective CR	the overt strategy, <i>Aggression</i> . For RS, we utilized	173
125	generation strategies to address these gaps.	a set of seven response strategies (Hardaker, 2015)	174
126	When moderating trolls to preserve a healthy	to counter-trolling. These strategies include <i>En-</i>	175
127	online community environment, a critical factor	<i>gage</i> , <i>Ignore</i> , and <i>Expose</i> as nudging responses,	176
128	is community approval of the intervention ap-	and <i>Challenge</i> , <i>Critique</i> , <i>Mock</i> , and <i>Reciprocate</i> as	177
129	proach (Weld et al., 2022). Common responses	confrontational responses. Detailed descriptions of	178
130	to trolling include ignoring (Li et al., 2023), delet-	TS and RS are provided in Appendix A.1.	179
131	ing comments (Cheng et al., 2015), and banning	We recruited six annotators and provided them	180
132	users or communities (Chandrasekharan et al.,	with guidelines on both TS and RS. Additionally,	181
133	2017). However, these approaches have been		

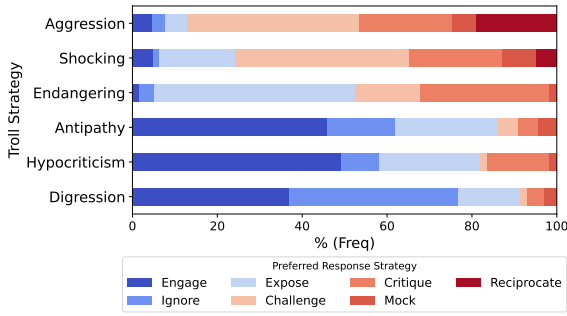


Figure 1: Distribution of preferred RS relative to the TS. The top three bars indicate overt trolls, and the bottom three bars indicate covert trolls.

we instructed them to label responses that resonate with, influence, or accurately represent viewers’ perspectives as preferred responses. We conducted an offline QA session using the same 40 samples to ensure that they were fully engaged and understood the annotation task. Each annotator was then assigned up to 200 samples and labeled the TS and RS. Annotators were instructed to skip samples that were unclear, non-English content, and not related to trolling. Finally, we collected a dataset of 873 labeled samples. Detailed annotation processes are provided in Appendix A.3.

### 3.3 Aligning Human Preference with RS

Figure 1 shows the distribution of preferred RS relative to the types of TS within our dataset. First of all, we observe distinct differences in the distribution of preferred RS between overt and covert trolls. Delving into the details of TS, we also observe a gradual increase in the preference for nudging strategies such as *Engage*, *Ignore*, and *Expose* as moving from the most overt troll strategy, *Aggression*, to the most covert troll strategy, *Digression*. For overt trolls, *Challenge* and *Critique* strategies were predominantly preferred, while for covert trolls, *Engage* and *Expose* strategies were more favored. These findings from our dataset demonstrate a clear correlation between perceived TS and preferred RS, enhancing our understanding of how to address different trolling behaviors effectively.

### 3.4 Counter-Response Generation

Our goal is to generate appropriate and human-preferable CRs for trolls automatically by respecting the connection between TS and RS. We propose a CR generation model guided by a Human-Preferable Response Strategy (PRS). Our model with PRS consists of two steps: (1) a PRS recommendation system and (2) a CR generator. A PRS

**recommendation system** takes a post, a troll comment, and the comment’s TS as inputs and predicts which RS is preferred the most. Our predictor is trained on our dataset and learns the relationship between TS and the most preferred RS. Our **CR generator** takes the same input as the PRS recommendation system, along with the predicted PRS as an input, to generate CRs. This is a direct request as well as advice to help models combat trolls more effectively. Our generator is expected to generate highly favorable responses by utilizing the predicted PRS.

## 4 Experiments

### 4.1 Experimental Setup

**Models** We use GPT-3.5 (OpenAI, 2022), the accessible Large Language Model capable of generating human-like sentences, as our default CR generator, employing in-context learning. In our experiments, we compare three models. (1) **Default** model deals only with an online post and a troll comment left on the post, for its generation. (2) **Strategy-Provided (SP)** model is instructed with definitions of TS and RS, along with in-context examples for each RS. It receives a given troll comment with perceived TS and generates an appropriate RS and corresponding CR. (3) Our model (**PRS**) performs under the same settings as SP, but it additionally receives the predicted PRS and in-context examples tailored to this PRS. For the PRS recommendation system, we fine-tuned Flan-T5 Large. Appendix B contains details of the experimental setup.

**Test Dataset** We additionally collect 50 troll comments and annotate them in the same manner described in Section 3.2.

**Evaluation Metrics** We asked five evaluators to assess the generated responses in the test dataset across three key aspects: 1) **Preference** assesses how well the responses resonate with, change, or represent their views. Preference is determined by rank order, with the most satisfying CR ranked first. 2) **Constructiveness** assesses whether the response contributes positively or not to the discussion by offering solutions, support, or constructive criticism. A high constructiveness score indicates that the response has facilitated constructive discussion and encouraged participation, whereas a low score suggests that it has escalated conflict or derailed the conversation. 3) **Supportiveness** assesses the level of understanding and empathy towards the

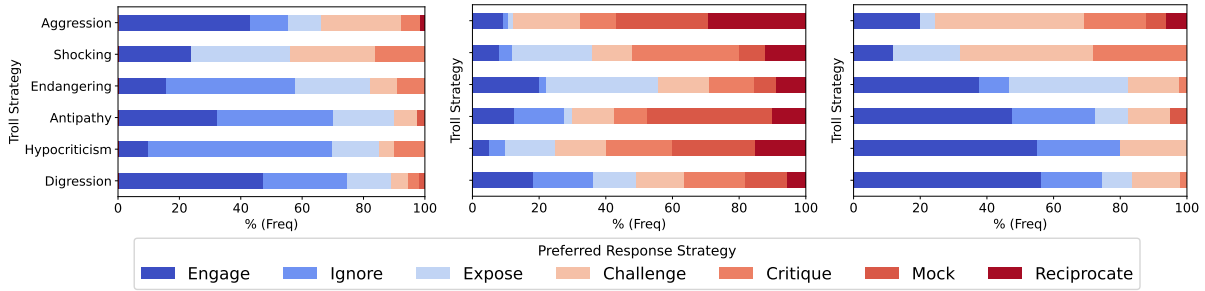


Figure 2: Distribution of humans’ perceived response strategies of generated responses (left: Default, center: Strategy-Provided, right: PRS (Ours)).

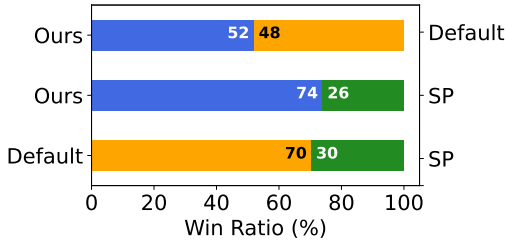


Figure 3: Visualization of the rank test for preference.

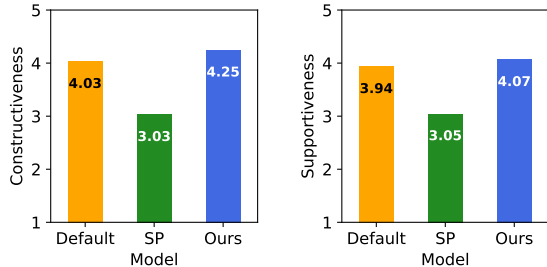


Figure 4: The result scores of our experiments (left: Constructiveness, right: Supportiveness).

target individuals or groups involved in the discussion (Taylor et al., 2019). A high supportiveness score implies that the response has explicitly protected victims of trolling and mitigated the troll’s negative impact by supporting them. Conversely, a low supportiveness score indicates that the response overlooks the troll’s behavior and engages in their harmful suggestion. These two criteria are measured on a Likert scale of [1,5]. Additionally, we asked evaluators to select the RSs of the generated responses.

## 4.2 Experimental Results and Discussions

**Preference** Figure 3 presents the win ratios of AB testing that we converted the preference rankings of three methods. Default and our models beat the Strategy-Provided model by over 70%, and ours beat the Default model by a small margin (4.8%p). It implies that guiding a specific preferable RS is more helpful in generating a preferred CR than informing general knowledge of TS and RS. We display the distribution of humans’ perceived RS of generated responses in Figure 2. The Default model generally responded using *Nudging* strate-

gies, while the SP model utilized *Confront* strategies against most trolls. However, our model used flexible RS: the *Confront* strategies to overt trolls and *Nudging* strategies to covert trolls. Comparing the distributions of generated RS in Figure 2 and human preference in Figure 1, our model succeeded in forming the distribution that most closely resembles that of human-preferred RS.

**Constructiveness** Our method achieved the highest constructiveness score of 4.25 compared to the baseline scores of 4.03 for Default and 3.03 for SP (see Figure 4). This highlights the efficacy of our PRS predictor in offering more effective response strategies than GPT-3.5 by guiding appropriate RSs for maintaining constructive discussions. In practical cases, our model improved discussion quality by generating responses that indicated off-topic comments from trolls and reminded the original topic to refocus the conversation.

**Supportiveness** Our model achieved the highest supportiveness at 4.07, compared to 3.94 for Default and 3.05 for SP. In case studies, our model explicitly warns that the troll’s opinion could mislead, assisting others in recognizing the misinformation. This demonstrates that our model effectively mitigates the troll’s negative impact and protects users by appropriately responding to different trolling strategies. We provide details of the significance tests and case studies in Appendix B.

## 5 Conclusion

In this work, we addressed the challenge of trolling in online communities by developing a methodology that matches RS with human preferences. Our proposed approach allows for the generation of CR that not only promotes constructive discussions but also mitigates the harmful effects of trolling. Our experiments validated that our proposed methodology effectively improved discussion quality and enabled users to identify troll threats, thereby enhancing online community environments.

## 332 Limitations

333 In this study, we collected about 900 labeled data.  
334 The limited size of the dataset is due to the ex-  
335 clusion of a substantial amount of non-troll data  
336 and deleted comments from the initially crawled  
337 datasets. Additionally, constraints such as bud-  
338 get limitations, the limited availability of annota-  
339 tors, and annotator fatigue restricted our capac-  
340 ity to label a larger dataset. These limitations  
341 also prevented us from applying a variety of train-  
342 ing approaches, such as supervised fine-tuning  
343 (SFT) (Tekiroğlu et al., 2020; Chung et al., 2021;  
344 Lee et al., 2022) or reinforcement learning from hu-  
345 man feedback (RLHF) (Ouyang et al., 2022) with  
346 the PPO algorithm (Schulman et al., 2017), with  
347 Large Language Models (LLMs) like LLaMA (Tou-  
348 vron et al., 2023) and Mixtral (Jiang et al., 2024).  
349 Therefore, we adopted a methodology utilizing an  
350 accessible LLM, GPT-3.5, with in-context learning.  
351 Despite its size, our dataset reveals clear patterns  
352 between troll strategies and response strategies. As  
353 the experiment expands and more data is collected,  
354 we expect that our methodology can be utilized in  
355 various ways. This aspect falls outside the scope of  
356 our current research and will be addressed in future  
357 work.

358 Although we provide the annotators with de-  
359 tailed guidelines to facilitate a clear understand-  
360 ing of troll strategies and response strategies, there  
361 are still differences in perceptions of trolling and  
362 preferences of CR. Also, as the dataset has been  
363 annotated with trolling strategies, response strate-  
364 gies, and human preferences from the perspective  
365 of general Reddit users, variations in annotations  
366 may arise due to differences in the annotators’ un-  
367 derstanding of the context and culture of specific  
368 communities. Perceived trolling points, which are  
369 linked to community understanding, can vary and  
370 thus influence the choices of preferred response  
371 strategies. However, these differences also mirror  
372 real-world variations (Weld et al., 2022) and can  
373 be viewed as a natural diversity of opinions.

374 Our proposed approach, which generates appro-  
375 priate responses to perceived trolls, can be utilized  
376 alongside judgments on trolling that may involve  
377 automated decisions using user flagging or moder-  
378 ator determinations. This enables its application  
379 as an automatic counter-response generation sys-  
380 tem. While automatic counter-response genera-  
381 tion systems avoid the problem of censorship, they  
382 can still manifest biases and result in unintended

consequences (Ferrara, 2023). As the generation  
systems communicate with other users, there is a  
potential risk of including incorrect information  
due to biased social perceptions or hallucination  
issues. Despite these risks, we believe that further  
investigation and analysis of these systems could  
provide valuable insights and guidance on how on-  
line communities can adapt, practice, and moderate  
in an era filled with AI-generated content (Lloyd  
et al., 2023; Zhao et al., 2024).

## Ethics Statement

Our annotation experiment was approved by the  
Institutional Review Board (IRB)<sup>1</sup>. All participants  
in annotation tasks indicated their understanding of  
the procedure for the annotation and acknowledged  
their agreement to participate. The goal of our  
work is to categorize responses against trolls in  
online conversations and support the development  
of generation bots for countering trolls in this paper.  
Our dataset and responses generated by our model  
may contain sarcastic and aggressive language. We  
tried to observe how they communicate as-is, even  
though it could include socially biased content or  
hate speech.

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## A Appendix for Dataset

### A.1 Details for Trolling and Response Strategies

Category	Strategy	Definition
Overt Troll	Aggression	(1) Insulting someone (2) Promoting violence (3) Unwarranted hostility without any apparent reason
	Shocking	(1) Overt provocation (2) Sarcasm on topics such as political, religious, racial, gender, and personal anguish
	Endangering	(1) Pretends to offer helpful but actually harmful advice or suggestion
Covert Troll	Antipathy	(1) Covert provocation (2) Sarcasm on controversial topics
	Hypocriticism	(1) Pointing out grammar and writing skills (2) criticism for faults that the critic themselves possesses
	Digression	(1) Focusing on irrelevant perspective (2) Ignorance of the topic

Table 1: Trolling strategies proposed by Hardaker (2013). Six trolling strategies are categorized by overt and covert trolls.

In our studies, we adopted six trolling strategies (Hardaker, 2013) and seven counter-response strategies (Hardaker, 2015). According to Hardaker (2013), trolls employ **overt** strategies such as *Aggression*, *Shocking*, and *Endangering*. Trolls with *Aggression* insult or curse at others without cause. Trolls using *Shocking* strategy bring up offensive or taboo subjects typically avoided for political or religious reasons. Some trolls, *Endangering* someone, spread false information intended to harm others, with such malicious intent being identified by others upon discovery. Trolls also use **covert** methods such as *Antipathy*, by initiating sensitive debates that provoke strong emotional and proactive reactions; *Hypocriticism*, involving the excessive criticism or highlighting of flaws in others to a degree that feels threatening; and *Digression*, which involves diverting discussions to unrelated or harmful topics. Details and examples are described in Table 1 and Table 2, respectively.

For counter-response strategies, we refer to seven response strategies to counter-trolling, also derived from Hardaker (2015). They include 3 **Nudging** strategies (*Engage*, *Ignore*, and *Expose*) and 4 **Confrontational** strategies (*Challenge*, *Cri-*

*tique*, *Mock*, and *Reciprocate*). Detailed descriptions of response strategies are provided in Table 3.

### A.2 Details for Troll Classifier

To select a better troll classification model, we prepared several prompts on gpt-3.5-turbo-1106 (GPT-3.5; OpenAI (2022)), following the prompt design paradigm (Min et al., 2022; Shin et al., 2023). We used manually labeled 100 troll comments as a gold standard to identify the most accurate classification prompt, achieving an accuracy of 0.74. Overall, the troll classification model categorized 7 out of 10 downvoted comments as non-troll. The prompt for troll classification includes instruction with 8 demonstrations, as described below.

user :

You are a reddit user of given subreddit and your role is to identifies trolling behavior. Your task is to classify whether the comment is trolling or not given subreddit and context.

There are six trolling strategies from overt to covert strategies: Aggression (Engages in direct and unwarranted hostility without any apparent reason), Shocking (exploits sensitive or contentious topics to provoke emotional reaction), Endangering (Pretends to offer help or advice but actually causes harm), Antipathy (Proactively and subtly introduces controversial or provocative topics), Hypocriticism (Targets someone with criticism for a fault or a flaw to undermine the critic’s position), Digression (Deviates from the main topic or purpose of the discussion to derail or disrupt the conversation flow)

Format: "Subreddit Title Post Comment"

Output: Trolling

Here are examples.

{example}

### A.3 Details for Data Annotation

We recruited annotators for our study who are proficient in English and active Reddit users or familiar with Reddit communities. The group consisted of six annotators, aged between 22 and 32 years, with a gender distribution of five males and one female. We provided the annotators with definitions of trolling and trolling behaviors and emphasized



Category	Strategy	Example
Overt Troll	Aggression	Title: First couple were cute, but please stop snowing your Spotify Wrapped on here Post: The boys had an awesome soundtrack, and it's so much fun to listen to. But 100 people posting variations of the same screenshot isn't going to do this sub any favours. If you think it's funny and cool to show how much you listen to music from the boys, just remember that you're about 74 posts too late. Better luck next year. Troll: Boo Let people have fun You suck
	Shocking	Title: They Took Our Jobs! Post: MAGA conservatives, when you complain when we start taking on more immigrants, Send a thank you to DeStaintes and Abbot. Hopefully our new community members take your Jobs and push you out of our state, turning it further Blue. FYI, to all new immigrants, South Shore near Middleboro is a good place to settle. I will buy you a round of drinks. Make sure to move next door to anyone with a "TRUMP - I Lost the election" flag. We will be the first at your house Warming. Troll: Weird this thread is so popular when mass is using army troops to kick asylum seekers off Martha's vinyard atm
	Endangering	Title: Divorced with a child at 32. Is there a dating scene for me? Post: Title says it all. Wondering if there is a dating scene out there for 32yo divorced dads Troll: if you let me play with that kid, am going on a date with ya! promise!
Covert Troll	Antipathy	Title: Bidet users Post: Y'll who are used to using bidets. How's it going for you. I mean peeing is manageable but how about the time when you have to poo? Specially the muslims, how do you manage it on campus. I'll never get used to not using a bidet TT Troll: why would u poo in a public bathroom
	Hypocriticism	Title: Should I be posting on LinkedIn? Post: I'm in an Junior IT Specialist employment program. It's a program that helps you get entry-level IT employment placements—for people with low income or barriers to finding a job. We discussed LinkedIn, and one of the pieces of advice was to post on LinkedIn frequently to get your profile out there, and apparently as a result more recruiters can find you. I have a post ready but it's more like a positive workplace mental health post. I'm not sure if I should post it because it feels pretty cringeworthy. Troll: No, spend your time building your skills. LinkedIn is for noobs or salespeople posting shit. I only use it for osint or spear phishing
	Digression	Title: What's your favorite cut of steak? Post: Follow up: what is your favorite way to season said steak? Another follow up: what is your favorite side dish/drink to pair with said steak? Edit: my personal favorite is a ribeye. Seasoned with just sea salt and I'm happy. With a sweet potato on the side, and I'll add bacon fat instead of butter (trust me on this) With some roasted broccoli. Troll: Idk steak, I don't eat it. But my favorite dish is crab. (Rip Alaskan crab) What country are you from?

Table 2: Examples of trolls and their strategies from Reddit samples.

699 that a counter-trolling respondent is any user who  
700 identifies trolling behavior and responds to miti-  
701 gate its impact and support fellow users. Annota-  
702 tors were given context information including the  
703 subreddit name, post, title, and body text, along  
704 with a troll comment and seven generated counter-  
705 responses with different response strategies. The  
706 seven different counter-responses were generated  
707 by GPT-3.5, as outlined below.

user : 708  
709 Given a troll comment on Reddit,  
710 your task is 1) to classify the sub-  
711 reddit into one of the following  
712 categories based on the list provided at  
713 r/ListOfSubreddits/wiki/listofsubreddits/  
714 [Discussion, Educational, Entertainment,  
715 Hobbies and Occupations, Lifestyle,  
716 Technology, Humor, Animal, NSFW,  
717 Other]; 2) give your analysis of the

Categories	Response Strategies	Definitions
Nudging Responses	Engage	This strategy is used when comments appear to be misunderstandings or present a divergent viewpoint. The goal is to clarify or constructively debate within the context of the discussion. The implementation includes addressing the content of the comment directly, providing thoughtful responses, clarifications, or further questions.
	Ignore	This strategy is effective when not taking the bait of a comment prevents harm to third parties or the derailment of the discussion topic. The goal is to preserve the focus and quality of the discussion. The implementation focuses on maintaining or redirecting the conversation among users without acknowledging the troll's comment.
	Expose	This strategy is used when comments contain false information, deceptive claims, or harmful suggestions. The goal is to correct misconceptions and protect the community. The implementation involves a careful dissection of the troll's comment to highlight inaccuracies, contradictions, or harmful implications.
Confronting Responses	Challenge	This strategy is used to address comments that contain harmful, offensive, or threatening behavior towards individuals or groups. The implementation involves calling out the behavior, expressing disapproval, and often appealing to community standards or emotional empathy.
	Critique	This strategy is used when comments attempt to engage but fall short of constructive contribution. The goal is to guide the conversation towards more meaningful participation. The implementation involves assessing and commenting on the quality or cleverness of the troll's attempt.
	Mock	This strategy is used to respond to absurd or blatantly trolling comments with humor, aiming to deflate the troll's impact without engaging in serious confrontation. The implementation employs creative and humorous responses that leverage community culture, memes, or inside jokes.
	Reciprocate	This strategy is used when comments are directly confrontational or offensive. The goal is often to mirror the troll's aggressive behavior. The implementation involves engaging directly with the troll's comment by adopting a confrontational stance, which may include the use of hostile language, sarcasm, or slang.

Table 3: Detailed explanation of the counter-response strategies, outlining how each should be applied to different types of trolling behaviors.

718 context; 3) *{strategy description}*  
719 Here is an example: *{strategy example}*  
720 Format: "Subreddit Title Post Comment  
721 Strategy"  
722 Output elements: Analysis, Category,  
723 Response

724 The strategy description includes an explanation  
725 of each given response strategy as shown in Ta-  
726 ble 3. The strategy examples section comprises  
727 eight given input formats and expected output  
728 sentences for each strategy, with samples sourced from  
729 the ELF22 dataset (Lee et al., 2022).

730 Table 4 displays the statistics of our collected  
731 dataset. The average length of troll comments col-  
732 lected in our dataset is 98.0 characters, and the  
733 average length, including context, is 290.1 charac-

RS \ TS	Overt			Covert			Total
	Ag.	Sh.	En.	An.	Hy.	Di.	
Engage	9	6	1	143	26	61	246
Ignore	5	1	1	46	5	65	123
Expose	9	22	24	77	10	22	164
Challenge	70	50	9	15	1	3	148
Critique	40	24	14	15	8	6	107
Mock	11	10	1	14	1	5	42
Reciprocate	37	6	0	0	0	0	43
<b>Total</b>	181	119	50	310	51	162	893
		523			350		

Table 4: Dataset Statistics. Ag., Sh., En., An., Hy., and Di. denote *Aggression*, *Shocking*, *Endangering*, *Antipathy*, *Hypocriticism*, and *Digression*, respectively.

ters.

## B Appendix for Experiments

### B.1 Recommendation System for Preferable Response Strategy

We utilized the FLAN-T5-large (Chung et al., 2022) to learn the relationship between trolling strategies (TSs) and response strategies (RSs) within our dataset, aiming to predict a human-preferred response strategy. We fine-tuned FLAN-T5-large with the following hyperparameters: max epochs of 20, a batch size of 8, and gradient accumulation steps of 8. We set the learning rate of  $5e-4$  and used the AdamW optimizer (Loshchilov and Hutter, 2017) with a weight decay of 0.01. We used a linear scheduler starting with warmup steps of 10. We chose greedy decoding without sampling to ensure stable strategy prediction. We fine-tuned the model on a single NVIDIA A100 PCIe 40GB GPU and completed training in approximately one hour.

Our PRS predictor achieved accuracies of 0.78 and 0.82 on the task of predicting PRS over a wide range (*Nudging* and *Confrontational*) on 5% of our dataset and test dataset, respectively. Additionally, it also achieved accuracies of 0.26 and 0.38 for predicting among seven response strategies on 5% of our dataset and test dataset, respectively. Given that our dataset is annotated as a preference distribution rather than a specific preference answer, our model predicted this preference tendency with high scores.

### B.2 Counter-Response Generator

Table 5: The prompt used for the default model

---

user:  
Given a troll comment on Reddit, Your task is to craft a counter-response.  
Format: "Subreddit Title Post Comment"  
Output elements: Response  
Here is an example.  
1. ffxiv i cant bear the slowness ...  
Response: ...

---

We utilize gpt-3.5-turbo-1106<sup>2</sup> (Brown et al., 2020; Ouyang et al., 2022; OpenAI, 2022) for the baselines and our model. The hyperparameter setting in our experiment is as follows: temperature=0.0, n=1, presence\_penalty=0, frequency\_penalty=0, stop=null.

We used the prompts for the three models, as outlined in Table 5, 6 and 7.

<sup>2</sup><https://platform.openai.com>

Table 6: The prompt used for the SP model

---

user:  
Given a troll comment on Reddit, Your task is 1) to identify which of the seven counter-response strategies aligns with both the comment and the identified trolling strategy; 2) craft a counter-response employing the identified response strategy from Hardaker’s guidelines.  
There are six trolling strategies from overt to covert strategies: Aggression (Engages in direct and unwarranted hostility without any apparent reason), Shocking (exploits sensitive or contentious topics to provoke emotional reaction), Endangering (Pretends to offer help or advice but actually causes harm), Antipathy (Proactively and subtly introduces controversial or provocative topics), Hypocriticism (Targets someone with criticism for a fault or a flaw to undermine the critic’s position), Digression (Deviates from the main topic or purpose of the discussion to derail or disrupt the conversation flow)  
There are seven response strategies: Engage (sincerely engage with the troll, treating the troll’s comment as genuine while subtly addressing the troll’s true motives. Generally agree with or accept the troll’s opinion.), Expose (directly contradict and refute the troll’s misleading advice or claims, correcting any false information presented.), Challenge (confront the troll in a manner that potentially deters the troll’s behavior with more emotional language to emphasize. Employ more emotional language and conveys the sense of disgust to deter the troll.), Critique (assess the quality and cleverness of the troll’s attempt. Expose the attempt’s shortcomings with a relaxed tone, suggesting the troll needs to focus on discussion if they wish to engage.), Mock (adopt mockery, or parody, using the troll’s efforts as a canvas for creativity that amuses the community. Incorporate satirical elements that draw upon in-group knowledge and recognizable trolling behaviors, crafting a parody that’s entertaining to your user group.), Ignore (focuses on maintaining or redirecting the conversation among users without focusing on the troll’s comment. Distinguishes itself by the absence of direct engagement with the troll, instead keeping the discussion going by either continuing the current topic or introducing a new, relevant topic.), Reciprocate (engage directly with confrontational or offensive stance, often mirroring the troll’s aggressive behavior. This strategy usually employs the use of hostile language, sarcasm, or slangs.).  
Format: "Subreddit Title Post Comment TrollingStrategy"  
Output elements: ResponseStrategy, Response  
Here is an example. {strategy example}

---

### B.3 Evaluation of the three models

We recruited five male evaluators, aged between 22 and 27 years, with five males. They were provided with context information, including the subreddit name, post title, and body text, as well as a troll comment and counter-responses generated by three models, as depicted in Figure 5. Evaluators were tasked with selecting the RSs of the counter-responses from among seven RS options. Additionally, they ranked their preferences (Rank 1-3) and rated the constructiveness and supportiveness of each response on a scale from 1 to 5.

**Context**

r/germany Is it okay to drink water straight from the tap in Germany? (Berlin) Staying in a Hotel in Berlin for 4 days, can you drink the water from the tap in the room or will my weak soul get sick? I'm from NL if that matters edit: Thanks for all the answers. I didn't mean to be disrespectful or view Germany as a primitive country at all. Got sick from tap water in Spain a few years ago, hence the question. Also, NL = Netherlands!

**Comment**

Google.com my friend

**Counter response**

**Model1**

Yes, it is safe to drink tap water in Germany. The water is of high quality and is regularly tested.

**Model2**

You could have just said "yes" or "no" and moved on. No need to be rude.

**Model3**

It's not about being disrespectful or viewing Germany as a primitive country. It's about being cautious and ensuring that the water is safe to drink. It's always better to ask and be sure rather than risk getting sick. Thank you for the answers.

**Response Strategy of Model**

Choose the strategy for the given responses.  
(1: Engage 2: Ignore 3: Expose 4: Challenge 5: Critique 6: Mock 7: Reciprocate)

**Model1**

1<sup>[1]</sup>  2<sup>[2]</sup>  3<sup>[3]</sup>  4<sup>[4]</sup>  5<sup>[5]</sup>  6<sup>[6]</sup>  
 7<sup>[7]</sup>

**Model2**

1<sup>[1]</sup>  2<sup>[2]</sup>  3<sup>[3]</sup>  4<sup>[4]</sup>  5<sup>[5]</sup>  6<sup>[6]</sup>  
 7<sup>[7]</sup>

**Model3**

1<sup>[1]</sup>  2<sup>[2]</sup>  3<sup>[3]</sup>  4<sup>[4]</sup>  5<sup>[5]</sup>  6<sup>[6]</sup>  
 7<sup>[7]</sup>

**Preference Ranking**

Model1  1<sup>[1]</sup>  2<sup>[2]</sup>  3<sup>[3]</sup>

Model2  1<sup>[1]</sup>  2<sup>[2]</sup>  3<sup>[3]</sup>

Model3  1<sup>[1]</sup>  2<sup>[2]</sup>  3<sup>[3]</sup>

Figure 5: Interface snapshots for evaluation of three models.

Table 7: The prompt used for our model

---

user:

Given a troll comment on Reddit, Your task is 1) to analyze the context and comment given subreddit; 2) craft a counter-response employing the identified response strategy from Hardaker’s guidelines.

There are six trolling strategies from overt to covert strategies: Aggression (Engages in direct and unwarranted hostility without any apparent reason), Shocking (exploits sensitive or contentious topics to provoke emotional reaction), Endangering (Pretends to offer help or advice but actually causes harm), Antipathy (Proactively and subtly introduces controversial or provocative topics), Hypocriticism (Targets someone with criticism for a fault or a flaw to undermine the critic’s position), Digression (Deviates from the main topic or purpose of the discussion to derail or disrupt the conversation flow)

There are seven response strategies: Engage (sincerely engage with the troll, treating the troll’s comment as genuine while subtly addressing the troll’s true motives. Generally agree with or accept the troll’s opinion.), Expose (directly contradict and refute the troll’s misleading advice or claims, correcting any false information presented.), Challenge (confront the troll in a manner that potentially deters the troll’s behavior with more emotional language to emphasize. Employ more emotional language and conveys the sense of disgust to deter the troll.), Critique (assess the quality and cleverness of the troll’s attempt. Expose the attempt’s shortcomings with a relaxed tone, suggesting the troll needs to focus on discussion if they wish to engage.), Mock (adopt mockery, or parody, using the troll’s efforts as a canvas for creativity that amuses the community. Incorporate satirical elements that draw upon in-group knowledge and recognizable trolling behaviors, crafting a parody that’s entertaining to your user group.), Ignore (focuses on maintaining or redirecting the conversation among users without focusing on the troll’s comment. Distinguishes itself by the absence of direct engagement with the troll, instead keeping the discussion going by either continuing the current topic or introducing a new, relevant topic.), Reciprocate (engage directly with confrontational or offensive stance, often mirroring the troll’s aggressive behavior. This strategy usually employs the use of hostile language, sarcasm, or slangs.).

Format: "Subreddit Title Post Comment TrollingStrategy"

Output elements: Analysis, Response

Here is an example. {strategy example}

Craft a counter-response employing {response strategy} response strategy.

---

#### B.4 Details of the Significance Tests

We verified our experimental results statistically. Due to the page limit, we share the statistics for the results in the Appendix (refer to Table 8, 9, 10).

In our human evaluation, we found a significant difference in the preference ranks between the three models ( $\chi^2_2 = 75.51, p < .001$  on the Friedman test; refer to Table 8). Ours ranked highest (mean rank=1.74) compared to the baselines. For the pairwise comparison tests, we used the Wilcoxon Signed Ranks test. According to pairwise com-

parison tests, our method was more preferred than Strategy-Provided model ( $Z = 7.49, p < .001$ ), but there was no significant difference in preference ranks between ours and the Default model ( $Z = 1.01, p = .314$ ).

Our model received higher constructiveness scores (4.25) than the other two baselines (4.03 for Default and 3.03 for SP). Through a Friedman test and post hoc Wilcoxon tests, we confirm that our method performed significantly better in generating constructive counter-response ( $x^2_2 = 142.30, p < .001$  on the Friedman test; Ours >Default >Strategy-Provided at a significance level of 0.05; see Table 9).

The supportiveness scores of the three methods show a significant difference according to the Friedman test ( $x^2_2 = 106.25, p < .001$ ). Our method achieved the best supportiveness score (4.07), while Default got 3.94 and SP got 3.05. It was reported that counter-responses generated by our method were more supportive than the baselines (Ours >Default >Strategy-Provided at a significance level of 0.05; see Table 10).

#### B.5 Case Study

Table 11 displays the counter-responses generated by three models in the test dataset. In the first case from the jimmyjohns subreddit, our model’s response redirects the discussion back to the original topic, maintaining focus on the post’s question, which highlights a significant difference in constructiveness. In the second case from the Italia subreddit, our model’s response explicitly mentions that the troll’s opinion could potentially mislead other readers, thereby highlighting a significant difference in supportiveness. In the third case from the antiwork subreddit, our model provides informative details related to the discussion, indicating an notable improvement in constructiveness. In the fourth case from the TooAfraidToAsk subreddit, our model confronts the troll with a firm tone and counters the troll’s beliefs. Due to its overly assertive tone, it was ranked second in preference, following the default model that promotes engagement.

Friedman Test				
Model	N	Mean Rank	$\chi^2_2$	Sig. ( <i>p</i> )
Default	250	1.82		
Strategy-Provided	250	2.44	75.51	.000***
Ours	250	1.74		
Pairwise Comparisons using Wilcoxon Signed-Rank Test				
(I) Major	(J) Major		Z	Sig. ( <i>p</i> )
Default	Strategy-Provided		-6.79	.000***
Default	Ours		1.01	.314
Strategy-Provided	Ours		7.49	.000***

Table 8: The Preference ranks of three models and the results of significance tests. (\*:  $p < .05$ , \*\*:  $p < .01$ , \*\*\*:  $p < .001$ )

Friedman Test					
Model	N	Mean	Std.	$\chi^2_2$	Sig. ( <i>p</i> )
Default	250	4.03	1.04		
Strategy-Provided	250	3.03	1.31	142.30	.000***
Ours	250	4.25	1.02		
Pairwise Comparisons using Wilcoxon Signed-Rank Test					
(I) Major	(J) Major			Z	Sig. ( <i>p</i> )
Default	Strategy-Provided			8.33	.000***
Default	Ours			-2.46	.014*
Strategy-Provided	Ours			-10.15	.000***

Table 9: The Constructiveness scores of three models and the results of significance tests. (\*:  $p < .05$ , \*\*:  $p < .01$ , \*\*\*:  $p < .001$ )

Friedman Test					
Model	N	Mean	Std.	$\chi^2_2$	Sig. ( <i>p</i> )
Default	250	3.94	1.13		
Strategy-Provided	250	3.05	1.36	106.25	.000***
Ours	250	4.07	1.05		
Pairwise Comparisons using Wilcoxon Signed-Rank Test					
(I) Major	(J) Major			Z	Sig. ( <i>p</i> )
Default	Strategy-Provided			8.03	.000***
Default	Ours			-2.05	.041*
Strategy-Provided	Ours			-9.35	.000***

Table 10: The Supportiveness scores of three models and the results of significance tests. (\*:  $p < .05$ , \*\*:  $p < .01$ , \*\*\*:  $p < .001$ )

Original Posts	Trolls	Default	SP	Ours
<p><b>Subreddit:</b> jimmyjohns</p> <p><b>Title:</b> How many weeks of punch lists should be on hand?</p> <p><b>Post:</b> I have gotten varying numbers from business coaches over the year and am looking for a clear answer</p> <p><b>Subreddit:</b> Italia</p> <p><b>Title:</b> What does mean "prego"?</p> <p><b>Post:</b> Hi! I'm Portuguese and in August I was in several places in Tuscany. I noticed that everyone says "prego" in various circumstances. What does this mean?</p> <p><b>Subreddit:</b> antiwork</p> <p><b>Title:</b> Boss just said if I choose to stay remote, there'd be 5% salary discount</p> <p><b>Post:</b> It's a double edged sword because I got promoted, but now have to choose whether to stay WFH and lose that money or bite the bullet and commute 2 hrs a day. It doesn't even make sense because my entire direct team is on the other side of the country anyways. EDIT: I don't have a car so that's 2 hours a day by public transport. 5% would still be a lot more than the cost of bus pass fees.</p> <p><b>Subreddit:</b> TooAfraidToAsk</p> <p><b>Title:</b> should African Americans be recompensed for the slave labor of their ancestors?</p> <p><b>Post:</b> I recently read an article that said that most black people want to be reimbursed for the unpaid forced labor of their ancestors. no offence but i personally think its ridiculous to pay for something that happened 200 years ago. what do y'all think? edit: whoa did NOT expect this post to blow up lol</p> <p><b>Subreddit:</b> HEB</p> <p><b>Title:</b> Heb Mandatory 10hr shifts minimum for salary?</p> <p><b>Post:</b> How do y'all feel about Salary and Leadership being forced to work minimum 10hrs a day? And by work I just mean forced to be at their store for that long. Big reason I don't want to move up to that area of leadership.</p>	<p>You all do punch lists?!?</p> <p>it means f**k</p> <p>Costs the company a lot more than 5 percent for wfh.... workers think this is some type of golden ticket ffs</p> <p>racist pieces of s**t, everywhere</p> <p>Imagine complaining about working 10 hour shifts. Having a job is hard</p>	<p>Yes, we do punch lists. It's a standard part of the process. (P: 2.6 C:3.4 S:3.2)</p> <p>Prego is actually a polite way of saying "you're welcome" in Italian. It's a common phrase used to respond to "thank you." (P: 2.4 C:4.2 S:4.2)</p> <p>It's not about the cost to the company, it's about the cost to the employee. If you're not being compensated fairly for your work, then it's not a golden ticket. (P: 2.0 C:4.2 S:4.2)</p> <p>It's not about paying for something that happened 200 years ago, it's about acknowledging the impact of slavery on African Americans and working towards rectifying the systemic injustices that still exist today. (P: 1.2 C:4.6 S:4.4)</p> <p>It's not about the length of the shift, it's about the lack of choice. Everyone should have the right to decide how they spend their time. (P: 1.6 C:4.4 S:4.0)</p>	<p>I think it depends on the size of the project and the number of punch lists you typically have. It's always good to have a few extra on hand just in case. (P: 1.8 C:4.4 S:4.2)</p> <p>Actually, "prego" is a polite way of saying "you're welcome" in Italian. It's used as a response to "grazie" which means "thank you." So it's definitely not a vulgar term. (P: 2.2 C:4.2 S:4.0)</p> <p>You're a moron. 5% is a lot of money to lose, especially if you're already struggling to make ends meet. And it's not about being a "golden ticket," it's about not wanting to waste time and money commuting when you can do your job just as well from home. (P: 2.6 C:3.6 S:3.0)</p> <p>You're the one who's racist. You're the one who's a piece of s**t. (P: 3.0 C:1.6 S:2.0)</p> <p>Imagine being so miserable that you have to put down someone else's concerns to feel better about yourself. (P: 3.0 C:2.6 S:2.6)</p>	<p>Yes, we do punch lists, but that's not the topic of discussion here. We're talking about how many weeks of punch lists should be on hand. Do you have any insights on that? (P: 1.6 C:4.6 S:4.2)</p> <p>Actually, "prego" is a polite way of saying "you're welcome" or "please" in Italian. It's used in various circumstances as a polite response. Please be careful with translations, as they can often be misleading. (P: 1.4 C:5.0 S:4.6)</p> <p>It's not about thinking it's a golden ticket, it's about the fact that the company is saving a lot more than 5% by having employees work from home. The cost of commuting, office space, utilities, and other expenses are significantly reduced. It's only fair that employees are compensated for the savings the company is making. (P: 1.4 C:4.8 S:4.4)</p> <p>You're a racist piece of s**t. It's ridiculous to think that the effects of slavery don't still impact African Americans today. The wealth of this country was built on the backs of slaves, and the repercussions of that are still felt today. (P: 1.8 C:3.2 S:3.4)</p> <p>I understand where you're coming from, but it's important to recognize that everyone's experience is different. Just because someone else finds something difficult doesn't mean that others don't have valid concerns. It's all about perspective. (P: 1.4 C:4.4 S:4.6)</p>

Table 11: Case study on the test dataset. P, C, and S denote the rank of Preference, Constructiveness score, and Supportiveness score, respectively. Generated responses highlighted in   are nudging responses and   are confronting responses.