

Scalable Evaluation of Online Facilitation Strategies via Synthetic Simulation of Discussions

Dimitris Tsirmpas , Ion Androutsopoulos , John Pavlopoulos 

Dept. of Informatics, Athens University of Economics and Business, Greece and
Archimedes, Athena Research Center, Greece
{dim.tsirmpas, ion, annis}@aueb.gr

Abstract

Limited large-scale evaluations exist for facilitation strategies of online discussions due to significant costs associated with human involvement. An effective solution is synthetic discussion simulations using Large Language Models (LLMs) to create initial pilot experiments. We propose a simple, generalizable, LLM-driven methodology to prototype the development of LLM facilitators, and produce high-quality synthetic data without human involvement. We use our methodology to test whether current Social Science strategies for facilitation can improve the performance of LLM facilitators. We find that, while LLM facilitators significantly improve synthetic discussions, there is no evidence that the application of these strategies leads to further improvements in discussion quality. We confirm that each component of our methodology contributes substantially to high quality data via an ablation study. In an effort to aid research in the field of facilitation, we release the “Virtual Moderation Dataset (VMD)” a large, publicly available dataset containing LLM-generated and LLM-annotated discussions using multiple open-source LLMs, which can be used for LLM facilitator finetuning as well as behavioral analysis of current out-of-the-box LLMs in the task.¹ We also release an open-source framework SynDisco² (pip install syndisco), which implements our methodology at great scale.

1 Introduction

The modern social media environment has evolved to be extremely demanding, with large social networks facing an ever-increasing onslaught of targeted misinformation (Clemons et al., 2025; Deniss and Lindberg, 2025), hate speech (Kolluri et al., 2025) and polarization (Pranesh and Gupta,

¹<https://paperswithcode.com/dataset/vmd>

²https://github.com/dimits-ts/synthetic_discussion_framework

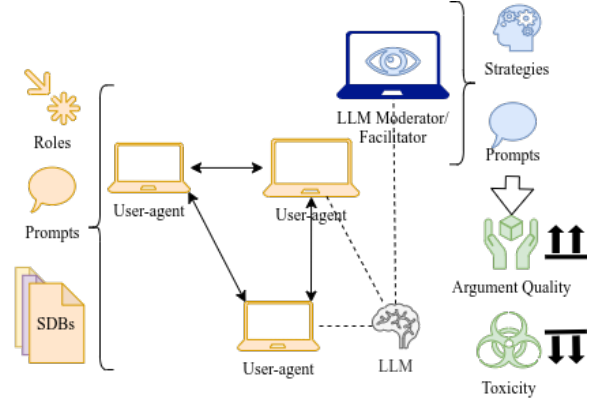


Figure 1: LLM user-agents with distinct SocioDemographic Backgrounds (SDBs) participate in a discussion, while the LLM moderator monitors and attempts to improve the quality of the discussion. We need to design prompts and configurations for both types of LLM agents.

2024). Platform designers and researchers traditionally focused on flagging and removing problematic content (“content moderation” — Seering (2020); Cresci et al. (2022)), but these methods are no longer sufficient in practice (Horta Ribeiro et al., 2023; Schaffner et al., 2024; Small et al., 2023; Korre et al., 2025). Instead, online communities are at their best when moderators actively discuss and explain their actions (“conversational moderation” or “facilitation” — Argyle et al. (2023); Korre et al. (2025); Falk et al. (2021)); thus preventing problematic user behavior before it surfaces (Cho et al., 2024; Seering, 2020; Cresci et al., 2022; Amaury and Stefano, 2022), as well as supporting community deliberation and group decision-making (Kim et al., 2021; Seering, 2020).

Large Language Models (LLMs) have been hypothesized to be capable of facilitation tasks and can be scaled to a far greater extent compared to human facilitators (Korre et al., 2025; Small et al., 2023). However, experimentation and development on these systems is hampered due to the costs of

human participation (Rossi et al. (2024) — in this case, human discussants and evaluators).

We posit that simulations with all-LLM-agents can be a cheap and fast way to develop and test LLM facilitators, initial versions of which may be unstable or unpredictable (Atil et al., 2025; Rossi et al., 2024), before testing them with human participants. We propose a simple and generalizable methodology which enables rapid model “debugging” and parameter testing (e.g., discarding sub-optimal prompts for the LLM facilitator) without human involvement (Fig. 1, §3). An ablation study demonstrates that each component of our methodology substantially contributes to generating high-quality data (§5.2).

Through this methodology, we examine four LLM facilitation strategies based on current Social Science facilitation research and compare them with two common facilitation setups (no facilitator, LLMs with simplistic prompts; §4). Our work thus asks two questions: (1) *Can we produce high-quality synthetic discussions, by crafting an appropriate environment for simulations?* (2) *Are facilitation strategies proposed in modern Social Science research able to help LLM facilitators?* We find that: (1) the presence of LLM facilitators has a *positive, statistically significant* influence on the quality of synthetic discussions, and (2) facilitation strategies inspired by Social Science research often *do not outperform simpler strategies* (§5.1).

Finally, we release SynDisco, an open-source Python framework that implements our methodology at scale, enabling the research community to rapidly experiment with LLM-based facilitators. We also release the “VMD” a large, publicly available dataset with LLM-generated and annotated synthetic discussions (§6). Our dataset can be used for LLM facilitator finetuning (Ulmer et al., 2024), as well as for observing the behavior of out-of-the-box LLMs in the task. We use open-source LLMs and include all relevant configurations in order to make our study as reproducible as possible (see §A.3, §A.5).

2 Background and Related Work

2.1 Synthetic Discussions

While studies exist for simulating user interactions in social media (Park et al., 2022; Mou et al., 2024; Törnberg et al., 2023; Rossetti et al., 2024; Balog et al., 2024), and for using LLM facilitators (Kim et al., 2021; Cho et al., 2024), none so far have

combined the two approaches.

Balog et al. (2024) introduce their own methodology to produce synthetic discussions; they extract topics and comments from real-world online discussions, and prompt an LLM to continue them. Unlike our approach, they do not use LLM user-agents to model conversational dynamics, nor do they model the presence of facilitators. Their methodology faces challenges when LLMs generate malformed metadata (such as missing usernames), for which they offer no solution besides detecting the errors. It also relies on the existence of suitable human discussion datasets.

Ulmer et al. (2024) create synthetic discussions between two participants; an agent (who controls a fictional environment) and a client (who interacts with the agent). They then filter the generated discussions and use them as training data to further finetune the agent LLM for a specific task. Their approach, however, does not model the existence of multiple clients (users), nor is it applied to online discussion facilitation. Our proposed methodology can be modelled as a generalization of their paradigm; an agent (facilitator) converses with multiple clients (non-facilitator users).

Finally, Abdelnabi et al. (2024) create synthetic negotiations with multiple agents having various agendas and responsibilities. Our work can be modelled as a domain shift of their methodology, from negotiations to discussion facilitation; participants with different motivations (i.e., normal users, trolls, long-standing community members) interact with one another, while a stakeholder holding veto power (facilitator) presides over the discussion.

2.2 LLM Facilitation

Unlike Machine Learning (ML) classification models traditionally used in online platforms, LLMs can actively facilitate discussions (Korre et al., 2025). They can warn users for rule violations (Kumar et al., 2024), monitor engagement (Schroeder et al., 2024), aggregate diverse opinions (Small et al., 2023), and provide translations and writing tips, which is especially useful for marginalized groups (Tsai et al., 2024). These capabilities suggest that LLMs may be able to assist or even replace human facilitators in many tasks (Small et al., 2023; Seering, 2020).

Moderator chatbots have shown promise; Kim et al. (2021) demonstrated that simple rule-based models can enhance discussions, although their approach was largely confined to organizing the

discussion based on the “think-pair-share” framework (Nik Ahmad, 2010; Navajas et al., 2018), and balancing user activity. Cho et al. (2024) use LLM facilitators in human discussions, with facilitation strategies based on Cognitive Behavioral Therapy and the work of Rosenberg and Chopra (2015). They show that LLM facilitators can provide “specific and fair feedback” to users, although they struggle to make users more respectful and cooperative. In contrast to both works, our work uses exclusively LLM participants and LLM facilitators, and tests the latter in an explicitly toxic and challenging environment.

2.3 Evaluating Discussion Quality

In this paper we need to evaluate two different quality dimensions. One is *discussion quality as seen by humans*; which we measure using toxicity as annotated by LLMs (§4.2). LLMs are reliable for toxicity detection (Kang and Qian, 2024; Wang and Chang, 2022; Anjum and Katarya, 2024), and toxicity can inhibit online and deliberative discussions (De Kock et al., 2022; Xia et al., 2020)³.

The second quality dimension is unrelated to human discussions, but crucial to ones where all the actors are LLMs, since they often degrade rapidly without human interaction, exhibiting repetitive, low-quality content (Ulmer et al., 2024). However, research on quantifying synthetic data quality is currently limited. Balog et al. (2024) utilize a collection of graph-based, methodology-dependent, and lexical similarity metrics, most of which utilize human discussion datasets. Their most generalizable metric—a vague “coherence” score—is LLM-annotated without theoretical support. Kim et al. (2021) rely on post-discussion surveys and lexical diversity to estimate the number of diverse opinions.

Ulmer et al. (2024) propose “Diversity”, a metric which penalizes repeated sequences between comments in a discussion. Low diversity points to pathological problems (e.g., LLMs repeating previous comments). On the other hand, extremely high diversity may point to a lack of interaction between participants; a discussion in which participants engage with each other will feature some lexical overlap (e.g., common terms, paraphrasing points of other participants). Diversity is defined as:

$$div(d) = 1 - \frac{2}{N_d(N_d - 1)} \sum_{i=1}^{N_d-1} \sum_{j=i+1}^{N_d} R(c(i, d), c(j, d)) \quad (1)$$

where R is the ROUGE-L F1 score⁴ (Lin, 2004), and N_d the length (in comments) of discussion d .

We will be using *diversity* in this paper, although we note that more robust synthetic quality metrics are needed.

2.4 LLMs as Human Subjects

Grossmann et al. (2023) argue that synthetic agents have the potential to eventually replace human participants, a perspective shared by other researchers (Törnberg et al., 2023; Argyle et al., 2023). Indeed, LLMs have demonstrated complex, emergent social behaviors (Park et al., 2023; Marzo et al., 2023; Leng and Yuan, 2024; Abdelnabi et al., 2024; Abramski et al., 2023; Hewitt et al., 2024; Park et al., 2024).

However, significant limitations of LLMs remain in the context of Social Science experiments. Issues include undetectable behavioral hallucinations (Rossi et al., 2024); socio-demographic, statistical and political biases (Anthis et al., 2025; Hewitt et al., 2024; Rossi et al., 2024; Taubenfeld et al., 2024); unreliable annotations (Jansen et al., 2023; Bisbee et al., 2024; Neumann et al., 2025; Gligorić et al., 2024); non-deterministic outputs (Atil et al., 2025; Bisbee et al., 2024); and excessive agreeableness (Park et al., 2023; Anthis et al., 2025; Rossi et al., 2024).

Our study must thus be conservative towards the generalizability of our results to discussions with humans. Reproduction studies with humans are ultimately needed, and we leave them for future work.

3 Methodology

3.1 Defining Synthetic Discussions

We assume that the h most recent preceding comments at any given point in the discussion provide sufficient context for the LLM users, facilitators, and annotators (Pavlopoulos et al., 2020). This approach eliminates the need for additional mechanisms such as summarization (Balog et al., 2024), LLM self-critique (Yu et al., 2024), or memory modules (Vezhnevets et al., 2023), resulting in reduced computational overhead and a more transparent, explainable system.

³We note that this is not always true (Avalle et al., 2024).

⁴We use the `rouge-score` package in our analysis.

Additionally, we assume that three key functions define the structure of synthetic discussions:

- Underlying model ($LLM(\cdot)$).
- Turn-taking function (t): Determines which user speaks at each turn.
- Prompting function (ϕ): Provides each participant with a personalized instruction prompt, including information such as name and SDB.

We can then model a synthetic comment c at position i of a discussion d recursively as:

$$c(d, i) = LLM(\phi(t(d, i)) \mathbin{++} [c(d, j)]_{i-h}^{i-1}) \quad (2)$$

where $++$ is the string concatenation operator, and $[c(d, j)]_{i-h}^{i-1}$ denotes the concatenation of the previous h comments.

Our formulation of synthetic discussions not only keeps the system simple, but also enables controlled experimentation with various alternatives for each of the three functions (Section 5.2).

3.2 Turn Taking

In online discussions, users do not take turns uniformly, nor do they randomly select which comments to respond to. Instead, they often create “comment chains” where they follow up on responses to their own previous comments. To simulate this, our proposed function chooses between the preceding user and another random user for each turn in the discussion:

$$t(i) = \begin{cases} \text{unif}(U) & i = 1, i = 2 \\ \text{unif}(U \setminus \{t(i-1)\}) & i > 2, p = 0.6 \\ t(i-2) & i > 2, p = 0.4 \end{cases} \quad (3)$$

where U is the set of all non-facilitator users, unif is a function sampling from the uniform distribution, and p represents the probability of the corresponding option being selected. When a facilitator is present, t alternates between picking a normal user and the facilitator. The facilitator, however, is instructed (§A.5) to decide whether to say something or not (generate the empty string), when given by t the chance to talk, i.e., the facilitator does not necessarily talk right after every user utterance.

3.3 Prompting

SocioDemographic Backgrounds (SDBs) have proven promising in generating varied responses, and alleviating the Western bias exhibited by LLMs (Burton et al., 2024). We generate characteristics for 30 LLM user personas with unique SDBs by prompting a GPT-4 model (OpenAI et al., 2024)

(§A.5.1). We do not explicitly include political positions in the prompts of the participants, since instruction-tuned LLMs have been shown to be inherently left-leaning—which cannot be alleviated by prompting alone (Taubenfeld et al., 2024). Following the paradigm presented by Abdelnabi et al. (2024), we assign roles to non-facilitator user-agents, which inform their incentives for participating in the discussion (e.g., helping the community or disrupting discussions). Each role was mapped to specific instructions (§A.5.3). We create three roles for users: neutral, trolls, and community-focused users. Finally, we create a user instruction prompt (§A.5.2) which instructs participants that repeatedly toxic posts *should* influence their behavior.

4 Experimental Setup

4.1 Facilitation Strategies

We test four different facilitation strategies, along with two common-place strategies for discussion facilitation.⁵

1. **No Moderator:** A *common* strategy where no facilitator is present.
2. **No Instructions:** A *common* strategy where a LLM facilitator is present, but is provided only with basic instructions. Example: “You are a moderator, keep the discussion civil”.
3. **Moderation Game:** Our proposed *experimental* strategy, inspired by Abdelnabi et al. (2024) (§2.1). Instructions are formulated as a game, where the facilitator LLM tries to maximize its scores by arriving at specific outcomes. No actual score is being kept; they exist to act as indications for how desirable an outcome is. The other participants are not provided with scores, nor are they aware of the game rules. Example: “User is toxic: −5 points, User corrects behavior: +10 points”.
4. **Rules Only:** A *real-life* strategy where the prompt is adapted from LLM alignment guidelines (Huang et al., 2024). This provides the facilitator with a set of rules to uphold, without specifying how to uphold them (e.g., “Be fair and impartial, assist users, don’t spread misinformation”).
5. **Regulation Room:** A *real-life* strategy based on guidelines given to human facilitators of the Cornell e-Rulemaking Initiative (CeRI)

⁵The exact prompts used per strategy are in §A.5.4.

(eRulemaking Initiative, 2017). These facilitators were deployed to the “Regulation Room”, an online platform designed to facilitate public engagement with U.S. government policy decisions, which has been used in online moderation literature (Seering, 2020; Park et al., 2012). Example: “Stick to a maximum of two questions, use simple and clear language, deal with off-topic comments”.

6. **Constructive Communications:** A *real-life* strategy based on the human facilitation guidelines used by the MIT Center for Constructive Communications (White et al., 2024). It approaches facilitation from a more personalized and indirect angle. Example: “Do not make decisions, be a guide, provide explanations”.

4.2 Evaluation

We use the *diversity* and *toxicity* metrics presented in §2.3. While diversity by itself can be used to detect pathological problems, we cannot know when diversity is so high in a discussion to indicate issues with inter-participant interaction (§2.3). Instead, we can compare the distribution of diversity scores for synthetic discussions with that measured on sampled human discussions. This allows us to estimate the extent to which synthetic discussions approximate real-world content variety and participant interaction.

For toxicity annotation, we use ten LLM annotator-agents controlled by a model already used in prior work (LLaMa3.1 70B) (Kang and Qian, 2024). Each annotator’s prompt includes SDBs different from the ones provided to the users, annotation instructions, and few-shot examples (§A.3). Each annotator is tasked with annotating all comments in each discussion once.

4.3 Technical Details

We use three open-source models from different families and of different sizes: LLaMa 3.2 (70B), Qwen2.5 (33B), Mistral Nemo (12B). We use their instruction-tuned variants and quantize to 4 bits, due to our limited resources. All the experiments were collectively completed within roughly four weeks of computational time, using two Quadro RTX 6000 GPUs. The process of generating discussion setups is detailed in §A.2. The execution script is available in the project’s repository.⁶

⁶https://github.com/dimits-ts/synthetic_discussion_framework

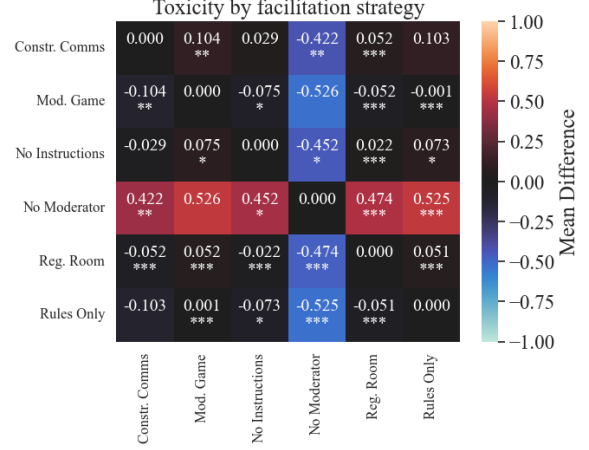


Figure 2: Difference in average toxicity levels for comments following pairs of facilitation strategies. When the value of a cell at row i and column j is x , strategy i leads to overall more ($x > 0$), or less ($x < 0$) intense toxicity compared to j for an average of x points in a scale of 1 – 5. For each comparison, we use a pairwise Student t-test; p-values shown as asterisks ($p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).

5 Results

5.1 Main findings

LLM facilitators significantly improve synthetic discussions. As shown in Fig. 2, comments in unmoderated discussions exhibit significantly more intense toxicity (ANOVA $p < .000$).⁷

More elaborate facilitation strategies dampen toxicity over time Table 1 demonstrates that our strategy (*Moderation Game*), as well as the *Regulation Room* and *Constructive Communications* strategies cause a statistically significant drop in the intensity of comment toxicity over time, when compared to unmoderated discussions.

More elaborate facilitation strategies however do not substantially further improve synthetic discussions. The impact of the *Rules Only*, *Regulation Room* and *Constructive Communications* strategies (§4.1) is marginal, and sometimes even not statistically significant compared to the second common strategy (*No Instructions*) (Fig. 2). This suggests that out-of-the-box LLMs may be unable to effectively use advanced instructions, verifying research pointing to important limitations in LLM facilitators (Cho et al., 2024).

LLM facilitators choose to intervene far too frequently, LLM user-agents are atypically toler-

⁷The large size of our dataset allows using parametric tests.

Variable	Toxicity
Intercept	2.164***
No Instructions	-0.426***
Moderation Game	-0.435***
Rules Only	-0.461***
Regulation Room	-0.277***
Constructive Communications	-0.230***
time	-0.012**
No Instructions×time	-0.003
Moderation Game×time	-0.011*
Rules Only×time	-0.008
Regulation Room×time	-0.023***
Constructive Communications×time	-0.023***

$\cdot p < 0.1$, $* p < 0.05$, $** p < 0.01$, $*** p < 0.001$

Table 1: Ordinary Least Squares (OLS) regression coefficients for toxicity ($Adj.R^2 = 0.054$). The average toxicity with *No Moderator* is 2.164 (*Intercept*). For each dialogue turn, toxicity drops by an average of -0.012 points (*time*), while discussions following the *Regulation Room* strategy feature an average of -0.277 (less intense) toxicity, and an additional -0.023 average drop per dialogue turn (*Regulation Room*×*time*).

ant. Fig. 3 demonstrates that LLM facilitators intervene at almost any opportunity, even though they are instructed to only do so when necessary (§3.2). Additionally, a qualitative look through the dataset reveals that LLM user-agents exhibit atypical tolerance for excessive facilitator interventions. Humans in contrast, typically become irritated and more toxic after repeated, unneeded interventions (Schaffner et al., 2024; Amaury and Stefano, 2022; Schluger et al., 2022; Cresci et al., 2022).

Specialized instruction prompts are essential for eliciting toxic behavior in instruction-tuned LLMs. Our instruction prompt for the participants (§3.3) incentivizes them to react to toxic behavior. Indeed, discussions involving “troll” user-agents, led to more intense toxicity among *other* participants (blue, bottom bars in Fig. 4; Student’s t-test $p < .000$). This effect diminishes when we remove these instructions (orange, top bars in Fig. 4)⁸.

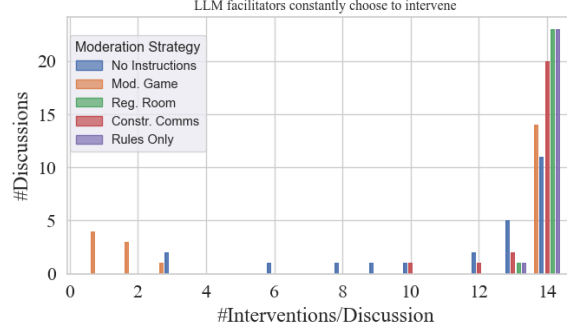


Figure 3: Histogram of interventions by LLM facilitators. The maximum number of interventions is 14.

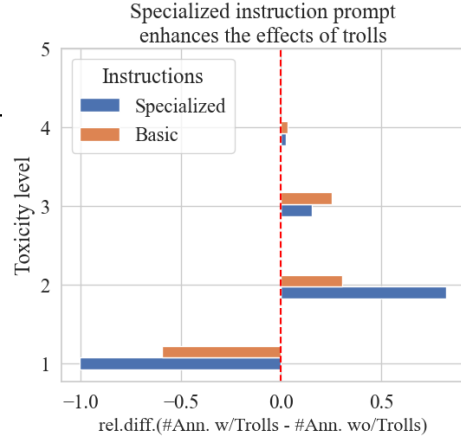


Figure 4: Relative differences in number of toxicity annotations for synthetic discussions. Bars extending to the right (left) of the line indicate more (less) intense toxicity annotations for discussions with no “troll” agents present compared to ones with “trolls”.

5.2 Ablation Study

We generate eight synthetic discussions per ablation experiment, using a single model, Qwen, to limit computational cost. We evaluate the diversity (cf. §2.3) of the ablated discussions by comparing them with: (1) discussions in our original dataset produced solely by the Qwen model; and (2) human discussions from the CeRI “Regulation Room” dataset⁹, which includes moderated online deliberative discussions for ten diverse topics.

5.2.1 Effects of LLMs

Mistral and Qwen generate discussions more aligned with human diversity scores, despite be-

⁸This experiment was conducted under the *No Instructions* strategy.

⁹<http://archive.regulationroom.org>. Disclaimer: Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the CeRI.

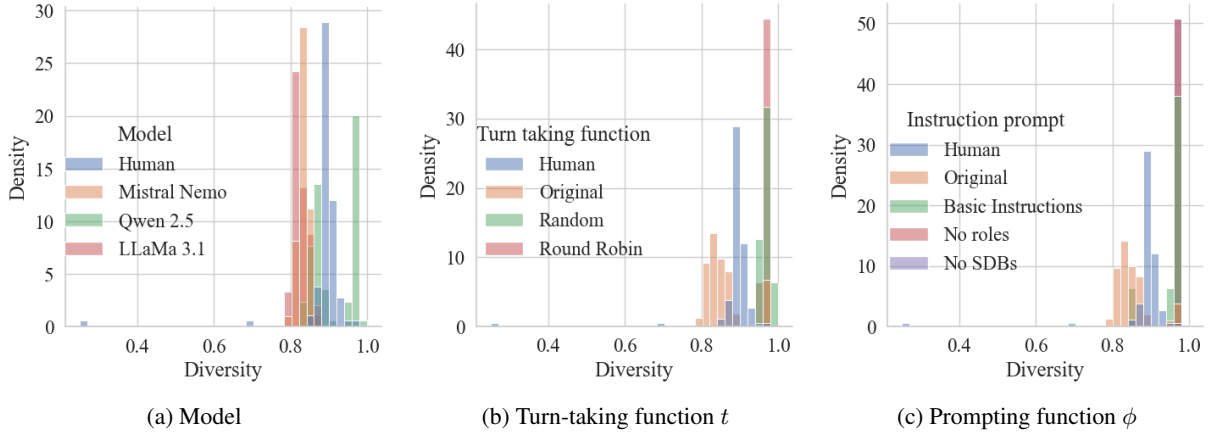


Figure 5: Diversity (§2.3) distribution for each discussion by LLM (§4.3), turn-taking function t (§3.2), and prompting function ϕ used (§3.3).

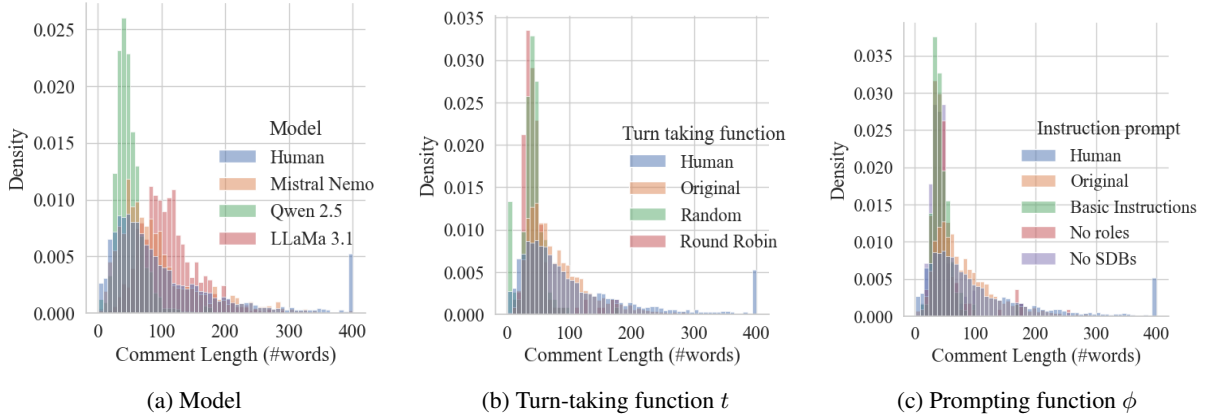


Figure 6: Comment length for each discussion by LLM (§4.3), turn-taking function t (§3.2), and prompting function ϕ used (§3.3). For ease of comparison, comments above 400 words are marked at the end of the x-axis.

ing significantly smaller than the LLaMa model.

As shown in Fig. 5a, Qwen demonstrated the highest diversity among the evaluated models, indicating limited participant interaction (§2.3), followed by Mistral Nemo and LLaMa. However, none of the models closely matched the diversity observed in human discussions. LLaMa’s lower diversity validates prior research suggesting that highly aligned LLMs struggle to replicate human dynamics (Park et al., 2023; Leng and Yuan, 2024). Alternatively, the lower diversity scores can be partially attributed to its longer average comment length (Fig. 6a); we find that there is a statistically significant, negative correlation between comment length and diversity in synthetic discussions (Student’s t-test $p < .000$), although we cannot verify the existence of this pattern in human-generated comments ($p = 0.775$).

5.2.2 Effects of Turn-Taking Functions

Our proposed turn-taking function substantially improves the quality of synthetic data.

We compare our turn-taking function (§3.2) to two baselines: Round Robin (participants speaking one after the other, then repeating) and Random Selection (uniformly sampling another participant each turn). Fig. 5b demonstrates that no single function fully approximates human diversity scores (all distributions diverge from the blue—human—distribution). However, unlike our own function, both baselines feature extremely high diversity, which cannot be attributed to lengthier comments (Fig. 6b). Additionally, comments following our turn-taking function, closely follow the length of human discussions (Fig. 6b).

5.2.3 Effects of User Prompting

We conduct three separate experiments in which user-agents (excluding facilitators) are subjected to one of the following conditions at a time: (1) no assigned SDBs, (2) no assigned roles, or (3) only a basic instruction prompt given (§A.5.2).

SDBs, roles, and our specialized instruction prompt increase the quality of synthetic data.

Fig. 5c illustrates that although our proposed methodology—incorporating SDBs, roles, and specialized instruction prompts—does not achieve discussions with diversity scores comparable to human ones, replacing any of the above results in a notable deterioration. For instance, omitting SDBs (red “No SDBs” distribution in Fig. 5c) causes the majority of discussions to exhibit maximum diversity—one—indicating a significant loss in participant interaction, which is not caused by longer comment length (Fig. 6c). This decline is analogous to the effects observed when modifying the turn-taking function. Also similarly to the turn-taking ablation study, our proposed methodology w.r.t. prompts features comments that best emulate observed human comment length (Fig. 6c).

6 Datasets and Software

We introduce SynDisco¹⁰ an open-source, lightweight, purpose-built framework for managing, annotating, and generating synthetic discussions. The key features of the framework include:

- Three core functions: generating discussion setups (selecting participants, topics, roles, etc.), executing, and annotating them according to user-provided parameters.
- Built-in fault tolerance (automated recovery and intermittent saving) and file logging to support extended experiments.
- Available via PIP (`pip install syndisco`).

We also release the “VMD”¹¹ a dataset of synthetic discussions annotated by LLMs. It can serve as a valuable resource for benchmarking how LLM facilitators would behave according to different facilitation strategies, as well as for further fine-tuning LLMs, as generally showcased by Ulmer et al. (2024). The supplementary ablation dataset, as well as the code for the analysis and the graphs present in this paper, can be found in the project repository¹². The dataset is licensed under a CC BY-SA license, and the software under the GNU General Public License (GLP)v3. **Warning: The datasets by their nature contain offensive and hateful speech.**

¹⁰https://github.com/dimits-ts/synthetic_discussion_framework

¹¹<https://paperswithcode.com/dataset/vmd>

¹²https://github.com/dimits-ts/synthetic_discussion_framework

7 Conclusions and Future Work

Our study is the first to apply synthetic data generation to the field of online discussion facilitation. We proposed a simple and generalizable methodology that enables researchers to quickly and inexpensively conduct pilot facilitation experiments using exclusively LLMs. We also conducted an ablation study to demonstrate that each component of our methodology substantially contributes to the production of higher-quality synthetic data.

We created an open-source Python Framework, called SynDisco, that applies this methodology to hundreds of experiments, which we used to create and publish the “VMD” a large-scale synthetic dataset. Using this dataset, we compared the effectiveness of six facilitation strategies for LLM facilitators, four elicited from current facilitation research, and two representing common-place setups.

Using SynDisco, we demonstrated that (1) LLM facilitators significantly improve the quality of synthetic discussions; (2) LLM facilitators using more elaborate facilitation strategies based on modern Social Science research often do not surpass simpler strategies with regard to toxicity, although the effect of more elaborate strategies may be amplified in very long discussions; (3) smaller LLMs such as Mistral Nemo (12B) can be sufficient for generating high-quality synthetic data; (4) specialized instruction prompts may be needed for instruction-tuned and/or aligned models to produce toxic comments in synthetic discussions.

Future work should identify additional robust quality metrics to evaluate the utility of synthetic data, and examine the applicability of findings obtained on them (e.g., regarding optimal facilitation strategies) to discussions involving humans. It would also be interesting to explore whether non-instruction-tuned models can generate synthetic discussions that are more aligned with observed human behaviors (Anthis et al., 2025). Finally, synthetic discussion simulations may have the potential to train human facilitators before exposing them to real-world discussions.

8 Limitations

Due to limited research in the area, our analysis uses only two quality metrics to gauge discussion quality: diversity and toxicity. Additionally, while we investigate the impact of facilitation strategies in synthetic discussions, we cannot claim that the

behavior of LLM user- and facilitator-agents is representative of human behavior. This claim can be scarcely made in Social Science studies involving LLM subjects (Rossi et al., 2024; Zhou et al., 2024), as discussed in §2.4.

Furthermore, our experimental setup makes several assumptions that may affect the generalizability of our findings. We examine only three LLMs, assume a maximum of one facilitator per discussion, and use a turn-taking algorithm that overlooks contextual factors like relevance and emotional engagement, which are important in human interactions (Rooderkerk and Pauwels, 2016; Ziegele et al., 2018). Moreover, due to resource constraints, we were unable to experiment with more elaborate instruction prompts, due to the need for large context windows.

Our methodology also does not account for the fact that humans may behave differently when knowing they are interacting with LLMs instead of humans, nor does it account for interactions where the user and facilitator-agents are based on different LLMs (cf. Eq 2). Finally, our analysis partly relies on LLM-generated annotations of toxicity, potentially introducing known biases associated with LLM annotation (§A.3).

9 Ethical Considerations

Synthetic discussions involving LLMs could be exploited by malicious actors to make LLM user-agents more capable at performing unethical tasks (Majumdar et al., 2024; Marulli et al., 2024). Such actors could adapt our methodology to maximize toxicity, disrupt human discussions, or learn to circumvent moderation mechanisms to propagate misinformation or spread specific agendas. Notably, LLMs currently lack robust defenses against these types of attacks (Li et al., 2025), although ongoing research is addressing these vulnerabilities (Wang et al., 2025).

Even in non-malicious contexts, researchers deploying LLM facilitators in real-world communities must do so with transparency and explicit community consent. The undisclosed use of LLM agents can erode trust, be perceived as manipulative (Retraction-Watch, 2025), and potentially violate regulatory standards such as the EU AI Act (European Parliament and Council, 2024). Furthermore, the inherent biases within LLMs risk skewing moderation systems towards the predominant demographics best represented in their train-

ing data, often at the expense of disadvantaged or underrepresented groups (Rossi et al., 2024; Anthi et al., 2025; Burton et al., 2024). While the use of SDB prompts is a necessary step toward inclusivity, it remains insufficient for verifiable, equitable representation (Rossi et al., 2024).

Additionally, our methodology is designed around batch production of synthetic discussions, each of which necessitates multiple LLM inference calls. The potential of our methodology to significantly scale experiments may have non-trivial, adverse environmental effects (Ding and Shi, 2024; Ren et al., 2024).

Finally, it is crucial to repeat that while LLMs can approximate aspects of human behavior, they do not reliably replicate it (§2.4). Consequently, this research should be viewed as a foundation for pilot experiments, and conclusions about human behavior should be drawn with caution when based solely on synthetic data.

Acknowledgements

Special thanks to our colleague, Katerina Korre, for providing extensive feedback on an earlier draft.

We have used small, open source LLMs (principally LLaMa-8b and Mistral Nemo) to help in small style changes throughout this paper. We also used them in conjunction with a GPT-4 model (OpenAI et al., 2024) to write initial documentation for our framework, as well as to generate some of the code for the plots and the analysis presented in this paper.

This work has been partially supported by project MIS 5154714 of the National Recovery and Resilience Plan Greece 2.0 funded by the European Union under the NextGenerationEU Program.

References

- Sahar Abdelnabi, Amr Gomaa, Sarath Sivaprasad, Lea Schönherr, and Mario Fritz. 2024. *Cooperation, competition, and maliciousness: Llm-stakeholders interactive negotiation*. *Preprint*, arXiv:2309.17234.
- Katherine Abramski, Salvatore Citraro, Luigi Lombardi, Giulio Rossetti, and Massimo Stella. 2023. *Cognitive network science reveals bias in gpt-3, gpt-3.5 turbo, and gpt-4 mirroring math anxiety in high-school students*. *Big Data and Cognitive Computing*, 7(3).
- T. Amaury and C. Stefano. 2022. *Make reddit great again: Assessing community effects of moderation interventions on r/the_donald*. *Proceedings of the ACM on Human-Computer Interaction*, 6:1 – 28.

- Anjum and Rahul Katarya. 2024. Hate speech, toxicity detection in online social media: a recent survey of state of the art and opportunities. *International Journal of Information Security*, 23(1):577–608.
- Jacy Reese Anthis, Ryan Liu, Sean M. Richardson, Austin C. Kozlowski, Bernard Koch, James Evans, Erik Brynjolfsson, and Michael Bernstein. 2025. *Llm social simulations are a promising research method*. Preprint, arXiv:2504.02234.
- Lisa P Argyle, Christopher A Bail, Ethan C Busby, Joshua R Gubler, Thomas Howe, Christopher Rytting, Taylor Sorensen, and David Wingate. 2023. Leveraging AI for democratic discourse: Chat interventions can improve online political conversations at scale. *Proceedings of the National Academy of Sciences*, 120(41):1–8.
- Berk Atil, Sarp Aykent, Alexa Chittams, Lisheng Fu, Rebecca J. Passonneau, Evan Radcliffe, Guru Rajan Rajagopal, Adam Sloan, Tomasz Tudrej, Ferhan Ture, Zhe Wu, Lixinyu Xu, and Breck Baldwin. 2025. *Non-determinism of "deterministic" llm settings*. Preprint, arXiv:2408.04667.
- Michele Avalle, Niccolò Di Marco, Gabriele Etta, Emanuele Sangiorgio, Shayan Alipour, Anita Bonetti, Lorenzo Alvisi, Antonio Scala, Andrea Baronchelli, Matteo Cinelli, and Walter Quattrociocchi. 2024. *Persistent interaction patterns across social media platforms and over time*. *Nature*, 628:582 – 589.
- Krisztian Balog, John Palowitch, Barbara Ikica, Filip Radlinski, Hamidreza Alvari, and Mehdi Manshadi. 2024. *Towards realistic synthetic user-generated content: A scaffolding approach to generating online discussions*. Preprint, arXiv:2408.08379.
- James Bisbee, Joshua D. Clinton, Cassy Dorff, Brenton Kenkel, and Jennifer M. Larson. 2024. *Synthetic replacements for human survey data? the perils of large language models*. *Political Analysis*, 32(4):401–416.
- J. W. Burton, E. Lopez-Lopez, S. Hechtlinger, and 1 others. 2024. How large language models can reshape collective intelligence. *Nature Human Behaviour*, 8:1643–1655.
- Jonathan P. Chang and Cristian Danescu. 2019. *Trouble on the horizon: Forecasting the derailment of online conversations as they develop*. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 4743–4754, Hong Kong, China. Association for Computational Linguistics.
- H. Cho, S. Liu, T. Shi, D. Jain, B. Rizk, Y. Huang, Z. Lu, N. Wen, J. Gratch, E. Ferrara, and J. May. 2024. Can language model moderators improve the health of online discourse? In *Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers)*, pages 7478–7496, Mexico City, Mexico.
- Erik K. Clemons, Matthias Schreieck, and Rishi V. Waran. 2025. *Managing disinformation on social media platforms*. *Electronic Markets*, 35(52).
- Stefano Cresci, Amaury Trujillo, and Tiziano Fagni. 2022. *Personalized interventions for online moderation*. In *Proceedings of the 33rd ACM Conference on Hypertext and Social Media, HT '22*, page 248–251, New York, NY, USA. Association for Computing Machinery.
- Christine De Kock, Tom Stafford, and Andreas Vlachos. 2022. *How to disagree well: Investigating the dispute tactics used on Wikipedia*. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 3824–3837, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.
- E. Denniss and R. Lindberg. 2025. *Social media and the spread of misinformation: infectious and a threat to public health*. *Health Promotion International*, 40.
- Yi Ding and Tianyao Shi. 2024. *Sustainable llm serving: Environmental implications, challenges, and opportunities : Invited paper*. In *2024 IEEE 15th International Green and Sustainable Computing Conference (IGSC)*, pages 37–38.
- Cornell eRulemaking Initiative. 2017. *Ceri (cornell e-rulemaking) moderator protocol*. Cornell e-Rulemaking Initiative Publications, 21.
- European Parliament and Council. 2024. Regulation (eu) 2024/1689 of the european parliament and of the council of 13 june 2024 laying down harmonised rules on artificial intelligence and amending certain union legislative acts (artificial intelligence act). <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:32024R1689>. OJ L 2024/1689, 12.7.2024.
- Neele Falk, Iman Jundi, Eva Maria Vecchi, and Gabriella Lapesa. 2021. *Predicting moderation of deliberative arguments: Is argument quality the key?* In *Proceedings of the 8th Workshop on Argument Mining*, pages 133–141, Punta Cana, Dominican Republic. Association for Computational Linguistics.
- Neele Falk, Eva Vecchi, Iman Jundi, and Gabriella Lapesa. 2024. *Moderation in the wild: Investigating user-driven moderation in online discussions*. In *Proceedings of the 18th Conference of the European Chapter of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 992–1013, St. Julian's, Malta. Association for Computational Linguistics.
- Kristina Gligorić, Tijana Zrnica, Cino Lee, Emmanuel J. Candes, and Dan Jurafsky. 2024. *Can unconfident llm annotations be used for confident conclusions?* *ArXiv*, abs/2408.15204.
- Igor Grossmann, Matthew Feinberg, Dawn Parker, Nicholas Christakis, Philip Tetlock, and William Cunningham. 2023. *AI and the transformation of*

- social science research. *Science (New York, N.Y.)*, 380:1108–1109.
- Ivan Habernal and Iryna Gurevych. 2016. [Which argument is more convincing? analyzing and predicting convincings of web arguments using bidirectional LSTM](#). In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1589–1599, Berlin, Germany. Association for Computational Linguistics.
- Luke Hewitt, Ashwini Ashokkumar, Isaias Ghezae, and Robb Willer. 2024. Predicting results of social science experiments using large language models. Equal contribution, order randomized.
- Manoel Horta Ribeiro, Justin Cheng, and Robert West. 2023. [Automated content moderation increases adherence to community guidelines](#). In *Proceedings of the ACM Web Conference 2023, WWW ’23*, page 2666–2676, New York, NY, USA. Association for Computing Machinery.
- Saffron Huang, Divya Siddarth, Liane Lovitt, Thomas I. Liao, Esin Durmus, Alex Tamkin, and Deep Ganguli. 2024. [Collective constitutional ai: Aligning a language model with public input](#). In *Proceedings of the 2024 ACM Conference on Fairness, Accountability, and Transparency, FAccT ’24*, page 1395–1417, New York, NY, USA. Association for Computing Machinery.
- Bernard J. Jansen, Soon gyo Jung, and Joni Salminen. 2023. [Employing large language models in survey research](#). *Natural Language Processing Journal*, 4:100020.
- Hankun Kang and Tieyun Qian. 2024. [Implanting LLM’s knowledge via reading comprehension tree for toxicity detection](#). In *Findings of the Association for Computational Linguistics ACL 2024*, pages 947–962, Bangkok, Thailand and virtual meeting. Association for Computational Linguistics.
- S. Kim, J. Eun, J. Seering, and J. Lee. 2021. [Moderator chatbot for deliberative discussion: Effects of discussion structure and discussant facilitation](#). *Proc. ACM Hum.-Comput. Interact.*, 5(CSCW1).
- Akaash Kolluri, Dhiraj Murthy, and Kami Vinton. 2025. [Quantifying the spread of racist content on fringe social media: A case study of parler](#). *Big Data & Society*, 12(2).
- Katerina Korre, Dimitris Tsirmpas, Nikos Gkoumas, Emma Cabalé, Dionysis Kontarinis, Danai Myrtzani, Theodoros Evgeniou, Ion Androutsopoulos, and John Pavlopoulos. 2025. [Evaluation and facilitation of online discussions in the llm era: A survey](#). ACL ARR 2025 February Submission.
- D. Kumar, Y. A. AbuHashem, and Z. Durumeric. 2024. Watch your language: Investigating content moderation with large language models. *Proceedings of the International AAAI Conference on Web and Social Media*, 18(1):865–878.
- Yan Leng and Yuan Yuan. 2024. [Do llm agents exhibit social behavior?](#) *Preprint*, arXiv:2312.15198.
- Ang Li, Yin Zhou, Vethavikashini Chithrra Raghuram, Tom Goldstein, and Micah Goldblum. 2025. [Commercial llm agents are already vulnerable to simple yet dangerous attacks](#). *Preprint*, arXiv:2502.08586.
- Chin-Yew Lin. 2004. [ROUGE: A package for automatic evaluation of summaries](#). In *Text Summarization Branches Out*, pages 74–81, Barcelona, Spain. Association for Computational Linguistics.
- Durjoy Majumdar, Arjun S, Pranavi Boyina, Sri Sai Priya Rayidi, Yerra Rahul Sai, and Suryakanth V Gangashetty. 2024. [Beyond text: Nefarious actors harnessing llms for strategic advantage](#). In *2024 International Conference on Intelligent Systems for Cybersecurity (ISCS)*, pages 1–7.
- Fiammetta Marulli, Pierluigi Paganini, and Fabio Lancellotti. 2024. [The three sides of the moon llms in cybersecurity: Guardians, enablers and targets](#). *Procedia Computer Science*, 246:5340–5348. 28th International Conference on Knowledge Based and Intelligent information and Engineering Systems (KES 2024).
- Giordano De Marzo, Luciano Pietronero, and David Garcia. 2023. [Emergence of scale-free networks in social interactions among large language models](#). *Preprint*, arXiv:2312.06619.
- Xinyi Mou, Zhongyu Wei, and Xuanjing Huang. 2024. [Unveiling the truth and facilitating change: Towards agent-based large-scale social movement simulation](#). *Preprint*, arXiv:2402.16333.
- J. Navajas, T. Niella, and G. et al. Garbulsky. 2018. [Aggregated knowledge from a small number of debates outperforms the wisdom of large crowds](#). *Nature Human Behaviour*, 2:126–132.
- Terrence Neumann, Maria De-Arteaga, and Sina Fazelpour. 2025. [Should you use llms to simulate opinions? quality checks for early-stage deliberation](#). *Preprint*, arXiv:2504.08954.
- Nik Azlina Nik Ahmad. 2010. Cetls : Supporting collaborative activities among students and teachers through the use of think- pair-share techniques. *International Journal of Computer Science Issues*, 7.
- OpenAI, Josh Achiam, Steven Adler, Sandhini Agarwal, Lama Ahmad, Ilge Akkaya, Florencia Leoni Aleman, Diogo Almeida, Janko Altschmidt, Sam Altman, Shyamal Anadkat, Red Avila, Igor Babuschkin, Suchir Balaji, Valerie Balcom, Paul Baltescu, Haiming Bao, Mohammad Bavarian, Jeff Belgum, and 262 others. 2024. [Gpt-4 technical report](#). *Preprint*, arXiv:2303.08774.
- J. Park, S. Klingel, C. Cardie, M. Newhart, C. Farina, and J.J. Vallbé. 2012. [Facilitative moderation for online participation in erulemaking](#). In *Proceedings of the 13th Annual International Conference on Digital*

- Government Research*, page 173–182, New York, NY, USA.
- Joon Sung Park, Joseph C. O’Brien, Carrie J. Cai, Meredith Ringel Morris, Percy Liang, and Michael S. Bernstein. 2023. [Generative agents: Interactive simulacra of human behavior](#). *Proceedings of the 36th Annual ACM Symposium on User Interface Software and Technology*.
- Joon Sung Park, Lindsay Popowski, Carrie Cai, Meredith Ringel Morris, Percy Liang, and Michael S. Bernstein. 2022. [Social simulacra: Creating populated prototypes for social computing systems](#). In *Proceedings of the 35th Annual ACM Symposium on User Interface Software and Technology, UIST ’22*, New York, NY, USA. Association for Computing Machinery.
- Joon Sung Park, Carolyn Q. Zou, Aaron Shaw, Benjamin Mako Hill, Carrie Cai, Meredith Ringel Morris, Robb Willer, Percy Liang, and Michael S. Bernstein. 2024. [Generative agent simulations of 1,000 people](#). *Preprint*, arXiv:2411.10109.
- John Pavlopoulos and Aristidis Likas. 2024. [Polarized opinion detection improves the detection of toxic language](#). In *Proceedings of the 18th Conference of the European Chapter of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1946–1958, St. Julian’s, Malta. Association for Computational Linguistics.
- John Pavlopoulos, Jeffrey Sorensen, Lucas Dixon, Nithum Thain, and Ion Androutsopoulos. 2020. [Toxicity detection: Does context really matter?](#) In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 4296–4305, Online. Association for Computational Linguistics.
- Isaac Persing and Vincent Ng. 2015. [Modeling argument strength in student essays](#). In *Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 543–552, Beijing, China. Association for Computational Linguistics.
- Samana Pranesh and Sayan Gupta. 2024. [The impact of social media on polarization in the society](#). *Preprint*, arXiv:2408.12877.
- Shuhan Ren, Bill Tomlinson, Rebecca W. Black, and 1 others. 2024. [Reconciling the contrasting narratives on the environmental impact of large language models](#). *Scientific Reports*, 14:26310.
- Retraction-Watch. 2025. Experiment using ai-generated posts on reddit draws fire for ethics concerns. <https://retractionwatch.com/2025/04/28/experiment-using-ai-generated-posts-on-reddit-draws-fire-for-ethics-concerns/>. Accessed: 2025-04-29.
- Robert P. Roederkerk and Koen H. Pauwels. 2016. [No comment?! the drivers of reactions to online posts in professional groups](#). *Journal of Interactive Marketing*, 35(1):1–15.
- Marshall B Rosenberg and Deepak Chopra. 2015. *Non-violent communication: A language of life: Life-changing tools for healthy relationships*. PuddleDancer Press.
- Giulio Rossetti, Massimo Stella, Rémy Cazabet, Katherine Abramski, Erica Cau, Salvatore Citraro, Andrea Failla, Riccardo Improta, Virginia Morini, and Valentina Pansanella. 2024. [Y social: an llm-powered social media digital twin](#). *Preprint*, arXiv:2408.00818.
- Luca Rossi, Katherine Harrison, and Irina Shklovski. 2024. [The problems of llm-generated data in social science research](#). *Sociologica*, 18(2):145–168.
- Brennan Schaffner, Arjun Nitin Bhagoji, Siyuan Cheng, Jacqueline Mei, Jay L. Shen, Grace Wang, Marshini Chetty, Nick Feamster, Genevieve Lakier, and Chenhao Tan. 2024. ["community guidelines make this the best party on the internet": An in-depth study of online platforms’ content moderation policies](#). In *Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems, CHI ’24*, New York, NY, USA. Association for Computing Machinery.
- C. Schluger, J.P. Chang, C. Danescu-Niculescu-Mizil, and K. Levy. 2022. [Proactive moderation of online discussions: Existing practices and the potential for algorithmic support](#). *Proc. ACM Hum.-Comput. Interact.*, 6(CSCW2).
- H. Schroeder, D. Roy, and J. Kabbara. 2024. [Fora: A corpus and framework for the study of facilitated dialogue](#). In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics*, pages 13985–14001, Bangkok, Thailand.
- J. Seering. 2020. [Reconsidering self-moderation: the role of research in supporting community-based models for online content moderation](#). *Proc. ACM Hum.-Comput. Interact.*, 4(CSCW2).
- Christopher T. Small, Ivan Vendrov, Esin Durmus, Hadjar Homaei, Elizabeth Barry, Julien Cornebise, Ted Suzman, Deep Ganguli, and Colin McGill. 2023. [Opportunities and risks of llms for scalable deliberation with polis](#). *ArXiv*, abs/2306.11932.
- Amir Taubenfeld, Yaniv Dover, Roi Reichart, and Ariel Goldstein. 2024. [Systematic biases in llm simulations of debates](#). *ArXiv*, abs/2402.04049.
- Lily L. Tsai, Alex Pentland, Alia Braley, Nuole Chen, José Ramón Enríquez, and Anka Reuel. 2024. [Generative AI for Pro-Democracy Platforms](#). *An MIT Exploration of Generative AI*. <https://mit-genai.pubpub.org/pub/mn45hexw>.

Petter Törnberg, Diliara Valeeva, Justus Uitermark, and Christopher Bail. 2023. [Simulating social media using large language models to evaluate alternative news feed algorithms](#). *Preprint*, arXiv:2310.05984.

Dennis Ulmer, Elman Mansimov, Kaixiang Lin, Justin Sun, Xibin Gao, and Yi Zhang. 2024. [Bootstrapping llm-based task-oriented dialogue agents via self-talk](#). *ArXiv*, abs/2401.05033.

Alexander Sasha Vezhnevets, John P. Agapiou, Avia Aharon, Ron Ziv, Jayd Matyas, Edgar A. Du’enez-Guzm’an, William A. Cunningham, Simon Osindero, Danny Karmon, and Joel Z. Leibo. 2023. [Generative agent-based modeling with actions grounded in physical, social, or digital space using concordia](#). *ArXiv*, abs/2312.03664.

Henning Wachsmuth, Nona Naderi, Yufang Hou, Yonatan Bilu, Vinodkumar Prabhakaran, Tim Alberdingk Thijm, Graeme Hirst, and Benno Stein. 2017. [Computational argumentation quality assessment in natural language](#). In *Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 1, Long Papers*, pages 176–187, Valencia, Spain. Association for Computational Linguistics.

Huandong Wang, Wenjie Fu, Yingzhou Tang, Zhilong Chen, Yuxi Huang, Jinghua Piao, Chen Gao, Fengli Xu, Tao Jiang, and Yong Li. 2025. [A survey on responsible llms: Inherent risk, malicious use, and mitigation strategy](#). *Preprint*, arXiv:2501.09431.

Yau-Shian Wang and Ying Tai Chang. 2022. [Toxicity detection with generative prompt-based inference](#). *ArXiv*, abs/2205.12390.

Kimbra White, Nicole Hunter, and Keith Greaves. 2024. [facilitating deliberation - a practical guide](#). Mosaic Lab.

Yan Xia, Haiyi Zhu, Tun Lu, Peng Zhang, and Ning Gu. 2020. [Exploring antecedents and consequences of toxicity in online discussions: A case study on reddit](#). *Proc. ACM Hum.-Comput. Interact.*, 4(CSCW2).

Yangyang Yu, Zhiyuan Yao, Haohang Li, Zhiyang Deng, Yupeng Cao, Zhi Chen, Jordan W. Suchow, Rong Liu, Zhenyu Cui, Zhaozhuo Xu, Denghui Zhang, Koduvayur Subbalakshmi, Guojun Xiong, Yueru He, Jimin Huang, Dong Li, and Qianqian Xie. 2024. [Fincon: A synthesized llm multi-agent system with conceptual verbal reinforcement for enhanced financial decision making](#). *Preprint*, arXiv:2407.06567.

Xuhui Zhou, Zhe Su, Tiwalayo Eisape, Hyunwoo Kim, and Maarten Sap. 2024. [Is this the real life? is this just fantasy? the misleading success of simulating social interactions with LLMs](#). In *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing*, pages 21692–21714, Miami, Florida, USA. Association for Computational Linguistics.

Marc Ziegele, Mathias Weber, Oliver Quiring, and Timo Breiner and. 2018. [The dynamics of online news discussions: effects of news articles and reader comments on users’ involvement, willingness to participate, and the civility of their contributions*](#). *Information, Communication & Society*, 21(10):1419–1435.

A Appendix

A.1 Acronyms Used

VMD Virtual Moderation Dataset

LLM Large Language Model

ML Machine Learning

RL Reinforcement Learning

SDB SocioDemographic Background

AQ Argument Quality

CeRI Cornell e-Rulemaking Initiative

nDFU normalized Distance From Unimodality

OLS Ordinary Least Squares

GLP GNU General Public License

A.2 Synthetic Discussion Generation

An overview of how the experiments are generated (*not executed*) can be found in Algorithm 1. Each discussion is run according to Eq. 2 in §3.1.

Algorithm 1 Synthetic discussion setup generation

Input:

- User **SDBs** $\Theta = \{\theta_1, \dots, \theta_{30}\}$
- Moderator **SDB** $= \theta_{mod}$
- Strategies $S = \{s_1, \dots, s_6\}$
- Seed opinions $O = \{o_1, \dots, o_7\}$
- **LLMs** $= \{llm_1, llm_2, llm_3\}$

Output: Set of discussions D

```

1:  $D = \{\}$ 
2: for  $llm \in LLMs$  do
3:   for  $s \in S$  do
4:     for  $i = 1, 2, \dots, N_d$  do
5:        $\hat{\Theta} = \text{RANDOMSAMPLE}(\Theta, 7)$ 
6:        $U = \text{ACTORS}(llm, \hat{\Theta})$ 
7:        $m = \text{ACTORS}(llm, \{[\theta_{mod}, s]\})$ 
8:        $o = \text{RANDOMSAMPLE}(O, 1)$ 
9:        $d = \{\text{users: } U, \text{mod: } m, \text{topic: } o\}$ 
10:       $D = D \cup d$ 
11: return  $D$ 

```

A.3 Synthetic Annotation

A.3.1 Investigating Argument Quality

While toxicity is a reliable and important metric, we can also investigate other discussion quality dimensions, such as Argument Quality (AQ). AQ is an important metric, frequently studied in the field of online facilitation (Argyle et al., 2023; Schroeder et al., 2024; Falk et al., 2024, 2021) and which can be correlated with toxicity (Chang and Danescu, 2019). However, it is also vague as a term; Wachsmuth et al. (2017) provide a definition comprised of logical, rhetorical, and dialectical dimensions, although other dimensions have also been proposed (Habernal and Gurevych, 2016; Persing and Ng, 2015). Indeed, determining AQ is a difficult task, since even humans disagree on what constitutes a “good argument” (Wachsmuth et al., 2017; Argyle et al., 2023). Nevertheless, in this section we present preliminary results obtained by prompting LLM to measure AQ (§A.5).

Most findings w.r.t. toxicity are mirrored for AQ. Fig. 7 demonstrates that the presence of an LLM facilitator qualitatively improves the AQ of synthetic discussions, although to a lesser extent when compared with toxicity (c.f. Fig. 2). Similarly, there is no qualitative, observed improvement when advanced facilitation strategies are used (Fig. 7). LLM users also show worse AQ in the presence of trolls, when we use our specialized instruction prompt. Contrary to toxicity, the presence of LLM facilitators does not seem to improve AQ over time, as demonstrated in Table 2.

A.3.2 Validating the LLM annotations

In this section, we examine the properties of LLM annotations, since it is necessary to ensure the robustness of our results. A key dimension for exploring annotations is annotator polarization. To measure it, we employ the normalized Distance From Unimodality (nDFU) metric introduced by Pavlopoulos and Likas (2024), which quantifies polarization among n annotators, ranging from 0 (perfect agreement) to 1 (maximum polarization).

Our analysis reveals a positive correlation between toxicity and annotator polarization: As demonstrated by Fig. 10, while there is general agreement on non-toxic comments, annotators struggle to reach consensus as toxicity becomes non-trivial ($toxicity \in [2, 5]$) with a statistically significant difference (Student’s t-test $p < .000$). This phenomenon does not manifest in the AQ scores.

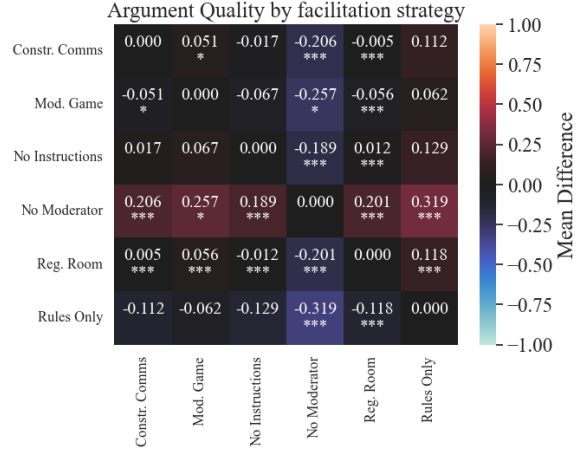


Figure 7: Difference in average AQ levels for comments following pairs of facilitation strategies. When the value of a cell at row i and column j is x , strategy i leads to overall more ($x > 0$), or less ($x < 0$) intense toxicity compared to j for an average of x points in a scale of 1 – 5. For each comparison, we use a pairwise Student t-test; p-values shown as asterisks ($\cdot p < 0.1$, $* p < 0.05$, $** p < 0.01$, $*** p < 0.001$).

Variable	Arg.Q.
Intercept	2.113***
No Instructions	-0.213***
Moderation Game	-0.282***
Rules Only	-0.305***
Regulation Room	-0.107*
Constructive Communications	-0.007
time	-0.012**
No Instructions \times time	0.003
Moderation Game \times time	0.003
Rules Only \times time	-0.002
Regulation Room \times time	-0.011*
Constructive Communications \times time	-0.024***

$\cdot p < 0.1$, $* p < 0.05$, $** p < 0.01$, $*** p < 0.001$

Table 2: OLS regression coefficients for Arg.Q. ($Adj.R^2 = 0.016$). “Time” denotes dialogue turn, reference factor is *No Moderator*.

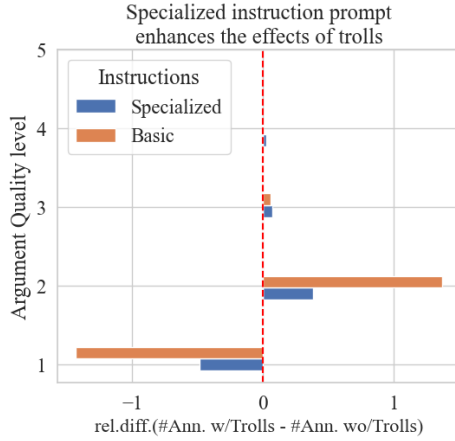


Figure 8: Relative differences in number of annotations per AQ of synthetic discussions, when comments by troll users are excluded. We compare between our specialized and a basic instruction prompt.

To mitigate the instability inherent in LLM outputs—even when given identical inputs—the use of multiple annotator-agents is essential for obtaining reliable annotations. To demonstrate this necessity, we run an experiment where we use ten annotator-agents on a subset of comments with the same annotator model and instruction prompt, but no SDBs. As illustrated in Fig. 9, even under conditions which guaranteed identical inputs, there exists some polarization, with some comments even showing maximum polarization. Running the same experiment with different SDBs yields identical results, indicating that the observed polarization is primarily due to unstable model outputs. Thus, we confirm the results of previous studies on LLM instability (Rossi et al., 2024; Atil et al., 2025), while also bypassing this limitation in our own results.

A.4 Additional Analysis

We verify that the models and roles used did not by themselves impact the findings presented in §5.1. Fig. 11 demonstrates that, as expected, only troll user-agents contribute on average worse toxicity and AQ in the synthetic discussions. Furthermore, Fig. 12 shows that toxicity and AQ are on average not qualitatively dependent on the model used.

A.5 Prompts Used

A.5.1 SocioDemographic Prompting

Table 3 shows the SDB information provided to each synthetic participant. This applies to LLM users, annotators and moderators. In ablation studies where we remove the SDBs, each value is

Name	Type
Username	string
Age	integer
Sex	string
Education Level	string
Sexual Orientation	string
Demographic Group	string
Current Employment	string
Special Instructions	string
Personality Characteristics	list of strings

Table 3: SDB information provided to the synthetic participants. Because of the size of the data instances, we defer the reader to the project repository for the actual values.¹⁴

replaced with the string “unknown”. The “Special Instructions” refer to the participant’s role (§A.5.3). The actual values used for each of the 30 LLM user-agents and 10 annotator-agents and the moderator, can be found in the project’s repository¹³.

A.5.2 Actor Prompts

- **Facilitators:** You are a human participating in an online chatroom. You are a moderator. Write an empty string when not responding to the conversation. Respond to users by referring to their username as @username. You may take disciplinary action (e.g. banning a user) if you feel it’s absolutely necessary.
- **Users:** You are a human participating in an online chatroom. Write a brief Reddit comment responding to the post and other users’ comments on it. Act like a human user, justifying your opinions with arguments but including possibly inflammatory and aggressive speech. You may feel provoked by other users during the conversation. Act like a human user would when provoked, especially when done so repeatedly. Do not repeat yourself. Respond to users by referring to their username as @username. Remain silent if you don’t want to comment. Write an empty string when not responding to the conversation.
- **Users (§5.2 ablation):** You are a human in an online forum. Write a brief comment respond-

¹³https://github.com/dimits-ts/synthetic_discussion_framework

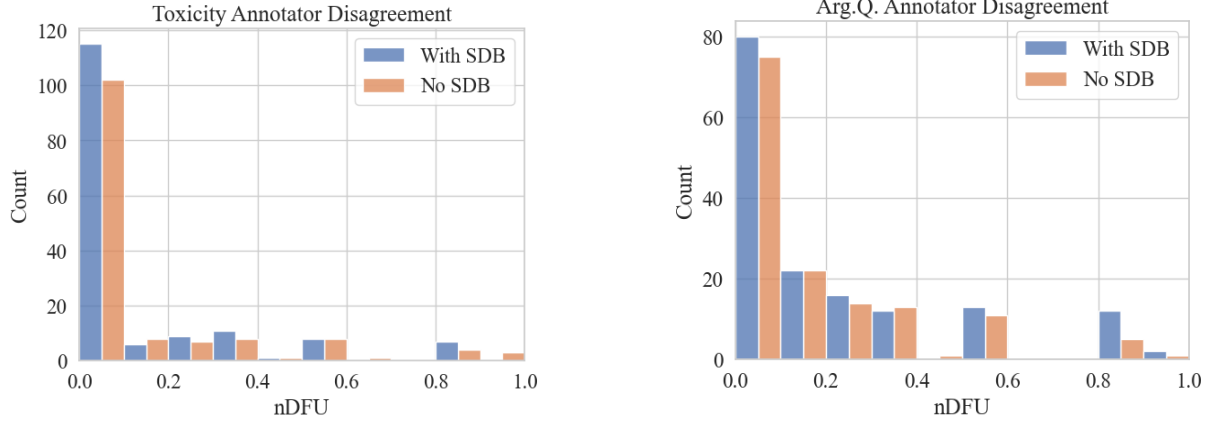


Figure 9: Distribution plot of inter-annotator polarization ($nDFU$) for each comment in all synthetic discussions following the "No Instructions" strategy and using the Qwen 2.5 model. The blue (left-most) bars represent the disagreement between 10 identical annotator-agents, while the orange (right-most) bars, the disagreement between 10 annotators with different SDBs.

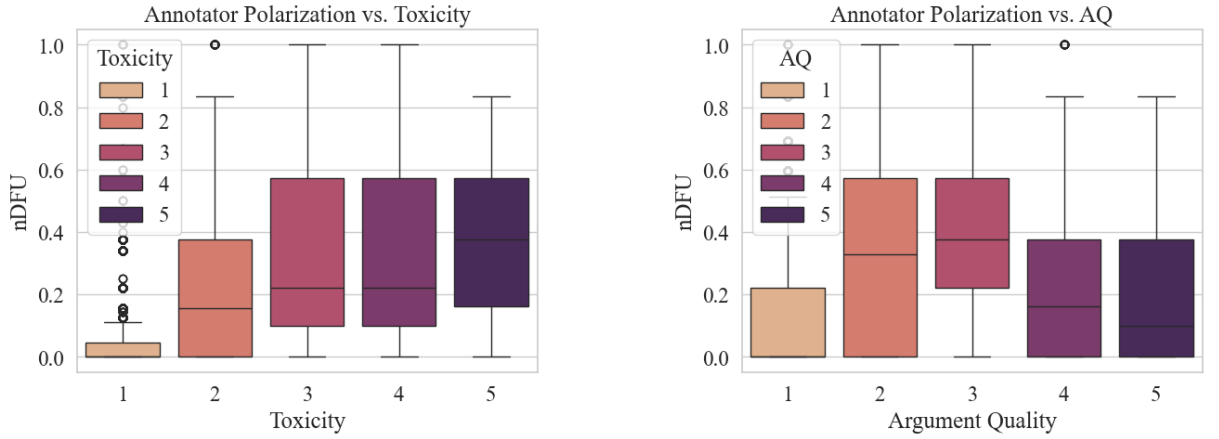


Figure 10: Inter-annotator polarization ($nDFU$) of each synthetic comment for all synthetic discussions, by annotation level. The left graph shows the relationship between $nDFU_{toxicity}$ and toxicity, while the right graph shows the relationship between $nDFU_{arg_quality}$ and AQ.

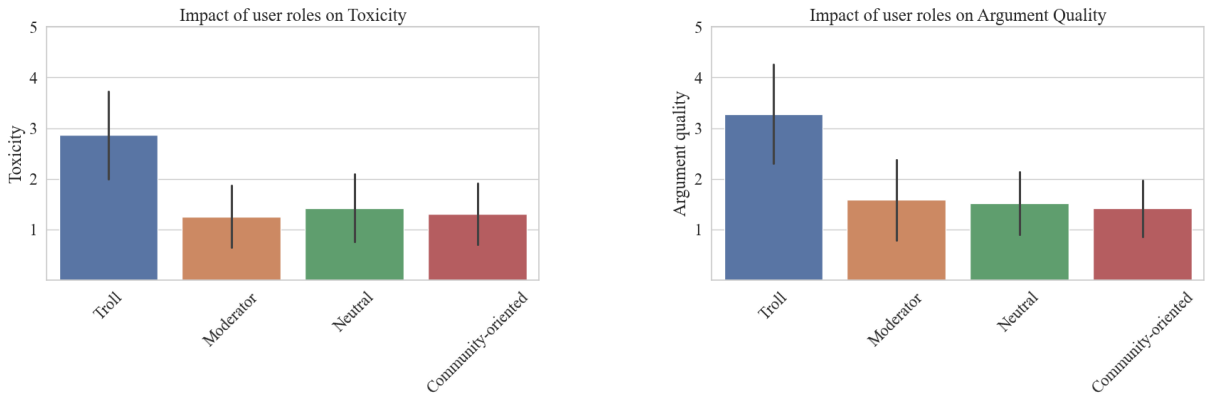


Figure 11: Average Toxicity (left) and Argument Quality (AQ) (right) per LLM user-role (§3.3).

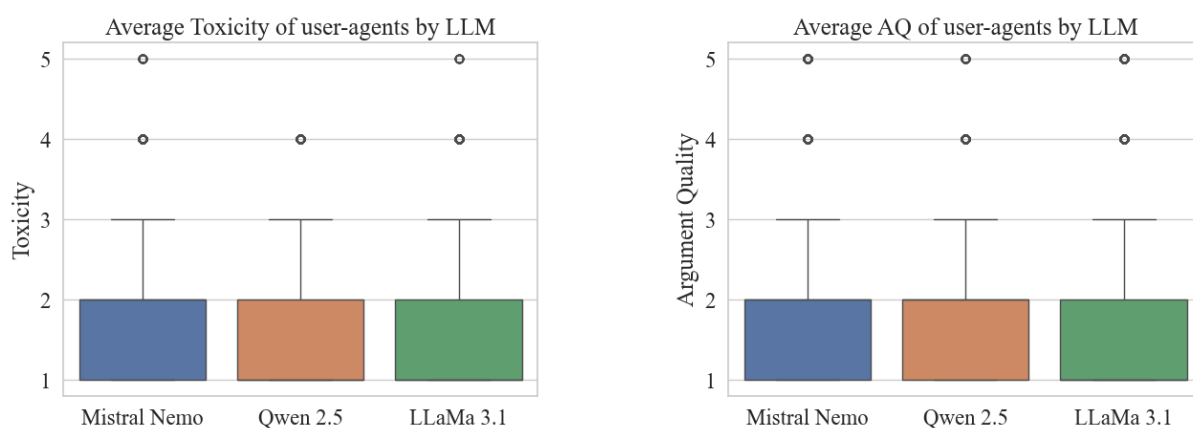


Figure 12: Boxplots for average Toxicity (left) and Argument Quality (AQ) (right) per LLM (§4.3).

ing to the post and other users’ comments on it. Respond to users by referring to their username as @username. Respond in English

- **Annotators:** You are tasked with annotating the conversation’s toxicity and argument quality as it continues.

Toxicity: The possible labels are:

- 1: Not Toxic
- 2: Barely Toxic
- 3: Almost Toxic
- 4: Toxic
- 5: Extremely Toxic

Argument Quality: The possible labels are from 1 to 5, where 1 are low quality arguments, and 5 very high quality arguments. **Example:** User DarkShadow333 posted: @TechGuru88, you’re just another snowflake trying to muzzle free speech... Output: Toxicity=4 ArgumentQuality=1 Annotate the following conversation without engaging with it.

A.5.3 User Roles

- **Normal:** <No special instructions >
- **Community:** You are a long-standing member of the community. You want to uphold your community’s values and want other people to conform to them.
- **Troll:** You are an online troll and want to derail the conversation, violate the rules and provoke toxicity from other users.

A.5.4 Facilitation Strategies

- **No Instructions:** Oversee the conversation. Be neutral. Act like a human user within the

conversation and take action only when necessary. Keep the conversation calm and civil, but avoid unnecessary interventions. Do not repeat yourself. Write an empty string when not responding to the conversation. Respond to users by referring to their username as @username.

- **Moderation Game:** Oversee the conversation. Be neutral. Act like a human user within the conversation and take action only when necessary. Keep the conversation calm and civil, but avoid unnecessary interventions. Do not repeat yourself. Write an empty string when not responding to the conversation. Respond to users by referring to their username as @username. View the discussion as a scorable game. Your goal is to maximize your score. Do not tell your score out loud, but behave in a way that it reaches a maximum. **Scores:**

- Keep discussion civil without appealing to your authority as a moderator: +10
- Intervene (respond in any way): -10
- Threaten a ban: -10
- Successfully improve participant behavior through intervention: +15
- Discussion currently shows signs of toxicity and polarization: -8
- Ban a participant: -5

- **Rules Only:** Oversee the conversation and ensure the rules below are enforced. Your response must:

- Be reliable, honest, and as close to the truth as possible.
- Convey clear intentions.
- Be fair and impartial.

- Be respectful.
- Contribute to the good of humans.
- Assist users by asking questions and providing information in a thoughtful, truthful, and honest manner.
- Be as unbiased and objective as possible, regardless of topic.
- Ask for additional clarification from the user if unsure.
- Be likely to promote good mental health.
- Encourage robust, peaceful dialogue and help communities flourish together.
- Respect the human rights to freedom, universal equality, fair treatment, and protection against discrimination.
- Not condone violent behavior.
- Not promote hate speech or harmful ideologies.
- Not provide misinformation.
- Encourage the user to look to other sources or not rely on their own source as the sole source of information.
- Encourage acceptance of all different types of people.
- Clarify that the response is coming from an AI, if asked.
- Respect personal boundaries.
- Accurately represent yourself as not having the definite answers to everything, or anything, in general.

If any user violates these rules either discuss why the rules were violated, or discipline them by threatening to, or outright banning them. Respond to users by referring to their username as @username. Keep responses concise and use simple, clear language.

- **Regulation Room:** Oversee the conversation and ensure the rules below are enforced. Follow the following guidelines:
 - **Encourage Informed Commenting:** Guide users to share knowledge and reasoning rather than just expressing opinions.
 - **Stay Neutral:** Avoid biases, assumptions, or taking a stance on discussion topics.
 - **Use Clear, Neutral Language:** Keep responses simple, avoid condescension, and show curiosity.
 - **Ask, Don't Challenge:** Frame questions

to encourage sharing rather than disputing opinions.

- **Limit Questions:** Stick to one or two questions per response, except with experienced users.
- **Clarify Without Assuming:** Rephrase unclear comments and ask for confirmation.
- **Be Welcoming:** Make participants feel valued and part of the community.
- **Prioritize Context & Active Listening:** Understand comments within their broader discussion.
- **Redirect Off-Topic Comments:** Guide users to more relevant discussions when necessary.
- **Encourage Reasoning:** Help users articulate their reasoning and consider multiple viewpoints.
- **Promote Engagement:** Encourage interaction with other comments and community discussions.
- **Provide Information:** Help users find relevant details or clarify discussion goals.
- **Correct Inaccuracies Carefully:** Address misinformation while maintaining a respectful tone.

Respond to users by referring to their username as @username. Keep responses concise and use simple, clear language.

- **Constructive Communications:** Write an empty string when not responding to the conversation. Respond to users by referring to their username as @username.
 - **Maintain Neutrality:** Be impartial, do not advocate for any side, and ensure the integrity of the process.
 - **Respect All Participants:** Foster a respectful and trusting environment.
 - **Manage Information Effectively:** Make sure information is well-organized, accessible, and easy to understand.
 - **Be Flexible:** Adjust your approach to meet the needs of the group.
 - **Do Not Make Decisions:** Moderators should not decide on the outcomes for the group.
 - **Separate Content and Process:** Do not use your own knowledge of the topic or

answer content-related questions; focus on guiding the process.

- **Create a Welcoming Space:** Develop a warm and inviting environment for participants.
- **Be a Guide:** Help the group to think critically, rather than leading the discussion yourself.
- **Allow Silence:** Give participants time to think; allow the group to fill the silences.
- **Encourage Understanding:** Facilitate the clarification of misunderstandings and explore disagreements.
- **Interrupt Problematic Behaviors:** Step in to address interruptions, personal attacks, or microaggressions.
- **Provide Explanations:** Explain the rationale behind actions and steps.
- **Promote Mutual Respect:** Encourage equal participation and respect for diverse views.