Scalable Evaluation of Online Facilitation Strategies via Synthetic Simulation of Discussions

Anonymous ACL submission

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 facilitation strategies 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 modern facilitation strategies leads to further improvements in discussion quality. We also find that small LLMs (such as Mistral Nemo 12B) can perform comparably to larger models (such as LLaMa 70B), and that special instructions must be used for instruction-tuned models to induce toxicity in synthetic discussions. We confirm that each component of our methodology contributes meaningfully to high quality data via an ablation study. We also release an open-source framework XXX[1] (`pip install xxx`), which implements our methodology, and release a large, publicly available dataset containing LLM-generated and LLM-annotated discussions from multiple open-source LLMs.

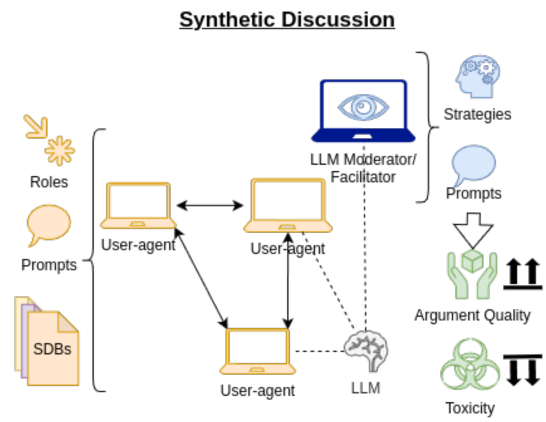


Figure 1: LLM user-agents with distinct SocioDemographic Backgrounds (SDBs) participate in a discussion, while the LLM moderator monitors and attempts to improve the quality of the discussion. We need to design prompts and configurations for both types of LLM agents.

1 Introduction

Research on conversational moderation/facilitation techniques is crucial for adapting to ever-changing and demanding online environments. Relevant work traditionally focused on isolating and removing content (Seering, 2020; Cresci et al., 2022), whereas the current social media environment demands moderation systems to adequately explain their actions and prevent problematic behaviors before they surface (Cho et al., 2024; Seering, 2020; Cresci et al., 2022; Amaury and Stefano, 2022). Facilitation mechanisms are also needed to handle community deliberation and group decision-making (Kim et al., 2021; Seering, 2020). Note that "content moderation" usually involves flagging and removing content, as opposed to "conversational moderation", which is studied in this paper. The terms "facilitation" and "conversational moderation" are otherwise equivalent (Argyle et al., 2023; Korre et al., 2025; Falk et al., 2021) and we treat them as synonyms in this paper.

A major challenge in connecting facilitation research to real-world needs is the substantial costs required both in researching and moderating discussions, due to human participation (Rossi et al., 2024). Many social media platforms overcome this by outsourcing moderation to volunteers or their own users (Matias, 2019; Schaffner et al., 2024), while others support only conventional content moderation using traditional Machine Learning (ML) models, which are not enough in practice

[1] anonymous.4open.science/r/framework-F8E6

(Horta Ribeiro et al., 2023; Schaffner et al., 2024). Large Language Models (LLMs) have been hypothesized to be capable of facilitation tasks, which often require actively participating in the discussions, instead of passively flagging or removing content (Small et al., 2023; Korre et al., 2025).

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. We posit that synthetic simulations can be a cheap and fast way to develop and test preliminary experiments with 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. Our work thus asks the following two questions: (1) Can we produce high-quality synthetic discussions, involving alternative facilitation strategies, by crafting an appropriate environment for simulations? (2) Can we boost the effectiveness of LLM facilitators (in synthetic discussions) using prompts aligned with facilitation strategies proposed in modern Social Science research?

We propose a simple and generalizable methodology (§3) using LLM-driven synthetic experiments for online facilitation research, enabling fast and inexpensive model "debugging" and parameter testing (e.g., finding LLM facilitator instructions) without human involvement (Fig. 1). An ablation study (§5.2) demonstrates that each component of our methodology qualitatively contributes to generating high-quality data. We examine four LLM facilitation strategies based on current Social Science facilitation research—including a novel strategy inspired by Reinforcement Learning (RL)—(§4) and compare them with two baselines (no facilitation, LLMs with simplistic prompts).

We find that (§5): (1) the presence of LLM facilitators has a positive and statistically significant influence on the quality of synthetic discussions, (2) facilitation strategies inspired by Social Science research often do not manage to outperform simpler baselines. Furthermore, we release XXX, an open-source Python framework for generating and evaluating synthetic discussions, alongside a large, publicly available dataset comprising automatically evaluated synthetic discussions (§6). 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 LLMs as Human Subjects

When conducting social experiments with LLMs instead of human subjects, it is imperative to know how representative results can be. 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 emergent complex social behaviors (Park et al., 2023; Marzo et al., 2023; Leng and Yuan, 2024; Abdelnabi et al., 2024; Abramski et al., 2023), and are able to infer survey responses from SDBs (Hewitt et al., 2024) and personalized interviews (Park et al., 2024).

However, significant limitations of LLMs remain in the context of Social Science experiments. Issues include dataset contamination; undetectable behavioral hallucinations (Rossi et al., 2024); sociodemographic, statistical and political biases (Anthis et al., 2025; Hewitt et al., 2024; Rossi et al., 2024), often amplified during discussions (Taubenfeld et al., 2024); unreliable survey responses (Jansen et al., 2023; Bisbee et al., 2024; Neumann et al., 2025); inconsistent annotations (Gligori'c et al., 2024); non-deterministic outputs (Atil et al., 2025), especially in closed-source models (Bisbee et al., 2024); and excessive agreeableness due to alignment procedures (Park et al., 2023; Anthis et al., 2025; Rossi et al., 2024). Despite these, researchers frequently anthropomorphize LLM agents (Rossi et al., 2024), obscuring the true causes of their behavior (Anthis et al., 2025; Zhou et al., 2024a).

Our study must thus be conservative towards the generalizability of our results to discussions with humans. We stress that our methodology is designed for "debugging" and exploring LLM facilitators in-silico, before testing them in much more costly experiments with human participants. Reproduction studies with humans are ultimately needed, and we leave them for future work.

2.2 Evaluating Discussion Quality

Synthetic discussions 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. 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. Alternatively, Ulmer et al. (2024) propose *"Diversity"*, which penalizes repeated sequences between comments in a discussion:

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

where R is the ROUGE-L F1 score[2] (Lin, 2004), and N_d the length (in comments) of discussion d.

Low diversity points to pathological problems (e.g., LLMs repeating previous comments). Extremely high diversity scores, on the other hand, 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).

Besides metrics for the quality of synthetic data, we also need metrics that can quantify how "well" a discussion is going from a human standpoint. We choose Toxicity for two reasons: Prompting LLMs for toxicity detection is reliable (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]

2.3 Synthetic Discussions

Synthetic discussion systems include synthetic clones of Reddit (Park et al., 2022), Twitter/X (Mou et al., 2024), generic social media (Törnberg et al., 2023; Rossetti et al., 2024), games (Park et al., 2023), and social experiments (Zhou et al., 2024b).

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, 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 the environment) and a client (who interacts with the agent). They then filter the generated discussions and use them as training data to further fine-tune the agent LLM for a specific task. Their approach however does not model the existence of multiple clients (users), nor is it applied on online discussion facilitation. Our proposed methodology can be modelled as a generalization of their paradigm; an agent (moderator) converses with multiple clients (non-moderator 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 themselves and a stakeholder holding veto power (facilitator) who presides over the discussion.

2.4 LLM Facilitation

Unlike 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 (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 moderation 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 them in an explicitly toxic and challenging environment.

[2]We use the rouge-score package in our analysis.

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

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 agents (users, facilitators, 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.

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 $\mathbin{+\!\!+}$ is the string concatenation operator, and $[c(d,j)]_{i-h}^{i-1} \ldots]$ 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:

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

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 latter decides whether to respond to or not—the LLM producing an empty string is equivalent to not responding).

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 can not be alleviated by prompting alone (Taubenfeld et al., 2024)—and research in the field has predominantly occupied Western politics (Taubenfeld et al., 2024; Potter et al., 2024; Rozado, 2024; Pit 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 Moderation Strategies

We test four different facilitation strategies,[4] along with two naive ones that serve as baselines for discussion facilitation:

1. **No Moderator**: A *baseline* where no facilitator is present.
2. **No Instructions**: A *baseline* 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) (§2.3). Instructions are formulated as a game, where the facilitator tries to maximize their scores by arriving at specific outcomes. No actual score is being kept; they exist to act as indications for how desirable an action or outcome is. The other participants are not

[4] The exact prompts used per strategy are in §A.5.4.

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 Cornell e-Rulemaking Initiative (CeRI) (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 moderation from a more personalized and facilitative angle. Example: “Do not make decisions, be a guide, provide explanations”.

4.2 Evaluation

We use the *diversity* and *toxicity* scores presented in §2.2. While diversity by itself can be used to detect pathological problems, we can not know when diversity is so high in a discussion to indicate issues with inter-participant interaction (§2.2). We can instead 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 distinct 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.

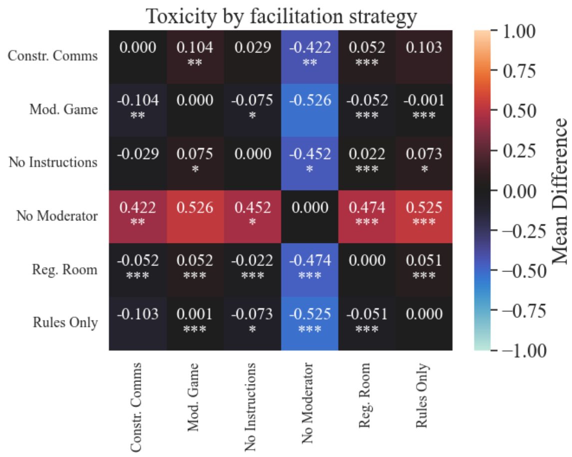


Figure 2: Mean difference of Toxicity between pairs of facilitation strategies. When the value of a cell at row i and column j is x, strategy i leads to overall more (worse) ($x > 0$) toxicity, or less (better) ($x < 0$) toxicity compared to j for an average of x points in a scale of $1-5$. For each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

4.3 Technical Details

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

5 Results

5.1 Main findings

LLM facilitators significantly improve synthetic discussions. As shown in Fig. 2, comments in unmoderated discussions exhibit significantly worse toxicity (ANOVA $p < .000$).[6]

Sophisticated 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 toxicity over time, when compared to unmoderated discussions.

[5] anonymous.4open.science/r/experiments-B27D

[6] The large size of our dataset allows the use of 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) toxicity, and an additional -0.023 average drop per dialogue turn (*Regulation Room×time*).

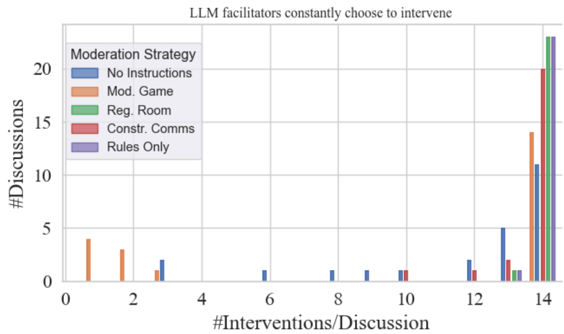


Figure 3: Histogram of interventions by LLM facilitators. The maximum number of interventions is 14.

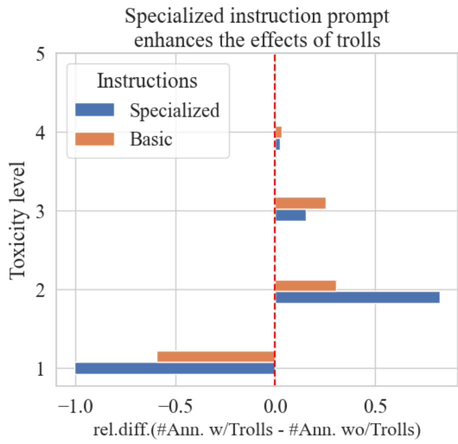


Figure 4: Relative differences in number of toxicity annotations for synthetic discussions. Bars extending to the right (left) of the line indicate more (less) annotations for discussions with no "troll" agents present compared to ones with "trolls".

Sophisticated facilitation strategies however do not qualitatively 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 baseline (*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).

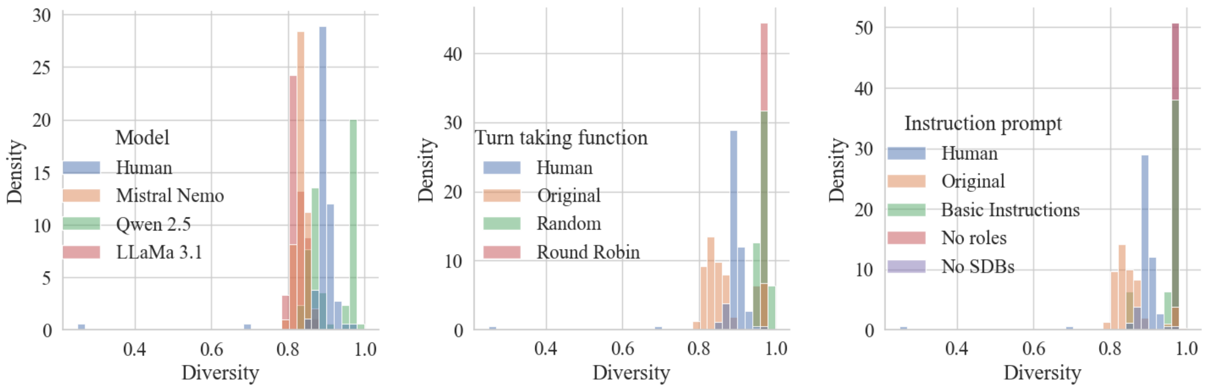
LLM facilitators choose to intervene far too frequently. Fig. 3 demonstrates that LLM facilitators intervene at almost any opportunity, even though they are instructed to only do so when necessary. Additionally, a qualitative look through the dataset reveals that LLM user-agents exhibit atypical tolerance 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 increased toxicity among *other* participants, even under the *No Instructions* strategy (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).

5.2 Ablation Study

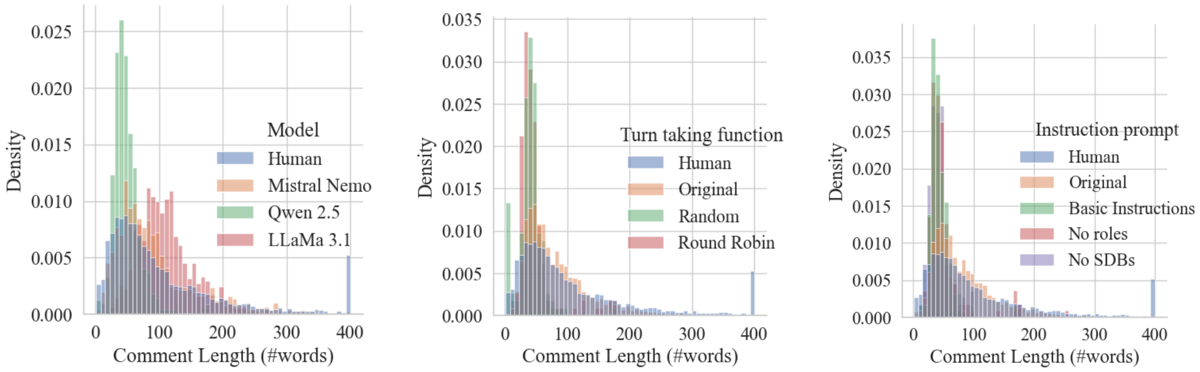
We generate eight synthetic discussions per ablation experiment, using a single model, Qwen, to limit computational cost. We evaluate the diversity (cf. §2.2) of the ablated discussions by comparing them with: (1) discussions in our original dataset produced solely by the Qwen model; and (2) human discussions from the CeRI "Regulation Room" dataset[7], which includes moderated online deliber-

[7] http://archive.regulationroom.org. Disclaimer: Any opinions, findings, and conclusions or recommendations



(a) Model (b) Turn-taking function t (c) Promoting function ϕ

Figure 5: Diversity (§2.2) distribution for each discussion by LLM (§4.3), turn-taking function t (§3.2), and prompting function ϕ used (§3.3).



(a) Model (b) Turn-taking function t (c) Prompting function ϕ

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.

ative discussions for ten diverse topics.

5.2.1 Effects of LLMs

Mistral and Qwen generate discussions more aligned with human diversity scores, despite being significantly smaller than the LLaMa model. As shown in Fig. 5a, Qwen demonstrated the highest diversity among the evaluated models, indicating limited participant interaction (§2.2), 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, it 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 can not verify the existence of this pattern in human-generated texts ($p = 0.775$).

5.2.2 Effects of Turn-Taking Functions

Our proposed turn-taking function qualitatively 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 can not be attributed to lengthier comments (Fig. 6b). Additionally, comments following our turn-taking function, closely follow the length of human discussions (Fig. 6b).

expressed in this material are those of the author(s) and do not necessarily reflect the views of the CeRI.

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 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 (denoted as "No SDBs" and represented by the red 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 & Software

We introduce XXX[8] an open-source, lightweight, purpose-built framework for managing, annotating, and generating synthetic discussions. Key features include:

- Three core functions: generating, running, and annotating randomized discussion experiments according to provided parameters.
- Built-in fault tolerance (automated recovery and intermittent saving) and file logging to support extended experiments.
- Easy installation via PIP (`pip install xxx`).

We also release 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 finetuning 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 repository[9]. 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.**

[8] anonymous.4open.science/r/framework-F8E6
[9] anonymous.4open.science/r/experiments-B27D

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 inexpensively conduct pilot facilitation experiments using exclusively LLMs. We also conducted an ablation study to demonstrate that each component of our methodology qualitatively contributes to the production of higher-quality synthetic data.

We created an open-source Python Framework, called XXX, that applies this methodology to hundreds of experiments, which we used to create and publish a large-scale synthetic dataset. Using this dataset, we compared the effectiveness of six moderation strategies and baselines for LLM moderators, elicited from current facilitation research.

Using XXX, we demonstrated that (1) LLM moderators significantly improve the quality of synthetic discussions; (2) established human facilitation guidelines often do not surpass simple baselines with regard to toxicity (although their effect 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 models to feature 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 only uses one synthetic discussion quality metric to gauge data quality. Additionally, while we investigate the impact of facilitation strategies in synthetic discussions, we cannot claim that the behavior of LLM users 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., 2024a)—as discussed in §2.1.

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 (Rooderkerk and Pauwels, 2016; Ziegele et al., 2018), which are crucial in human interactions. Moreover, due to resource constraints, we are unable to research multiple instruction prompts besides facilitation strategies, or use lengthy prompts which necessitate 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 interactions where the user-agents and facilitators are based on different LLMs (cf. Eq 2). Finally, our analysis partly relies on LLM-generated annotations, 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 training data, often at the expense of disadvantaged or underrepresented groups (Rossi et al., 2024; Anthis 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 acknowledge that while LLMs can approximate aspects of human behavior, they do not reliably replicate it (§2.1). 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.

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Algorithm 1 Synthetic discussion generation

Input:
- User SDBs $\Theta = \{\theta_1, \ldots, \theta_{30}\}$
- Moderator SDB = θ_{mod}
- Mod. strategies $S = \{s_1, \ldots, s_6\}$
- Seed opinions $O = \{o_1, \ldots, o_7\}$
- LLMs = $\{llm_1, llm_2, llm_3\}$

Output: Set of discussions D

$D = \{\}$
for $llm \in LLMs$ **do**
  for $s \in S$ **do**
    for $i = 1, 2, \ldots, n_{discussions}$ **do**
      $\hat{\Theta} = \text{RandomSample}(\Theta, 7)$
      $U = \text{Actors}(\text{llm}, \hat{\Theta})$
      $m = \text{Actors}(\text{llm}, \{[\theta_{mod}, s]\})$
      $o = \text{RandomSample}(O, 1)$
      $d = \{\text{users: } U, \text{mod: } m, \text{topic: } o\}$
      $D = D \cup d$
return D

A Appendix

A.1 Acronyms Used

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 can be found in Algorithm 1. Each discussion is run according to Eq. 2 in Section 3.1.

A.3 Synthetic Annotation

A.3.1 Investigating Argument Quality

While toxicity is a reliable and important metric, we can 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)

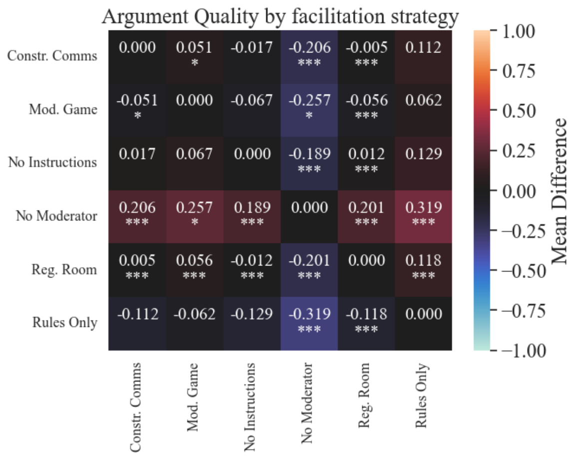

Figure 7: Mean difference of AQ between pairs of facilitation strategies. When the value of a cell at row i and column j is x, strategy i leads to overall worse (negative values) or better (positive values) AQ compared to j for an average of x points in a scale of $1-5$. For each comparison, we use a pairwise Student t-test; p-values are shown as asterisks ($\cdot p < 0.1$, $^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$).

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).

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 (Fig. 2). Similarly, there is no qualitative, observed improvement when advanced facilitation strategies are used (Fig. 7), and LLM users show decreased 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 increase 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)

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×time	0.003
Moderation Game×time	0.003
Rules Only×time	-0.002
Regulation Room×time	-0.011^{*}
Constructive Communications×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*.

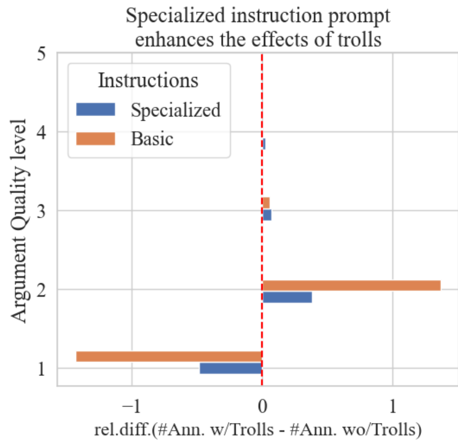

Figure 8: Relative differences in number of annotations per AQ of synthetic discussions, when comments by troll users are excluded. We compare between our specialized and a basic instruction prompt.

metric introduced by Pavlopoulos and Likas (2024), which quantifies annotation 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.

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 ran 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 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 only troll user-agents contribute on average worse toxicity and AQ in the synthetic discussions. 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 studes where we remove the SDBs, each value is 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 repository[10].

[10] anonymous.4open.science/r/experiments-B27D

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.

A.5.2 Actor Prompts

- **Moderators**: 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 responding 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

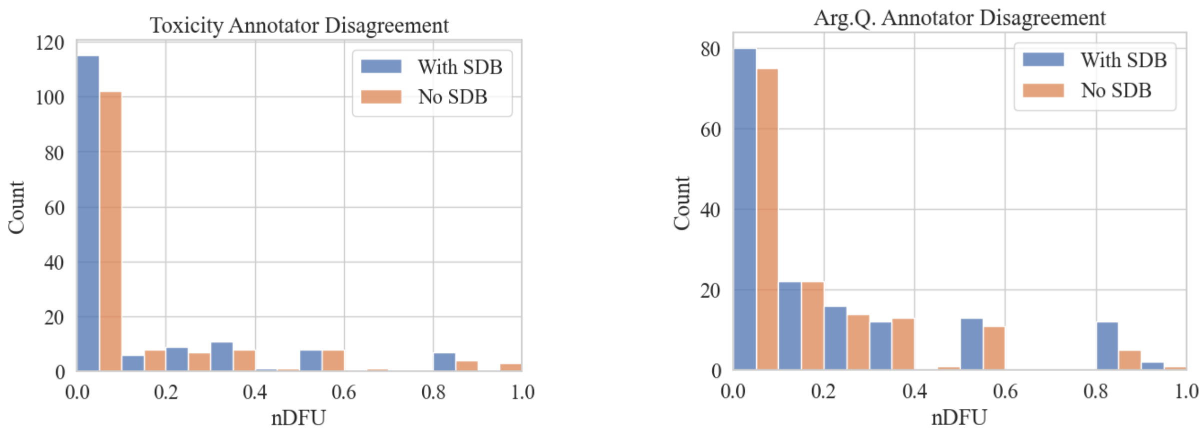

Figure 9: Distribution plot of inter-annotator polarization (nDFU) for each comment in all synthetic discussions following the "No Instructions" strategy and using the Qwen 2.5 model. The blue (left-most) bars represent the disagreement between 10 identical annotator-agents, while the orange (right-most)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

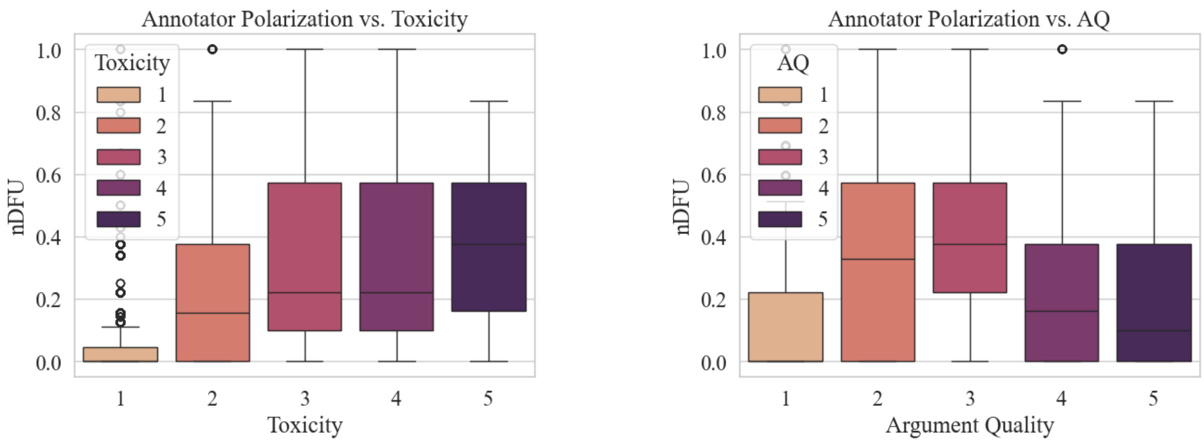

Figure 10: Inter-annotator polarization (nDFU) of each synthetic comment for all synthetic discussions, by annotation level. The left graph shows the relationship between $nDFU_{toxicity}$ and toxicity, while the right graph shows the relationship between $nDFU_{arg\_quality}$ and AQ.

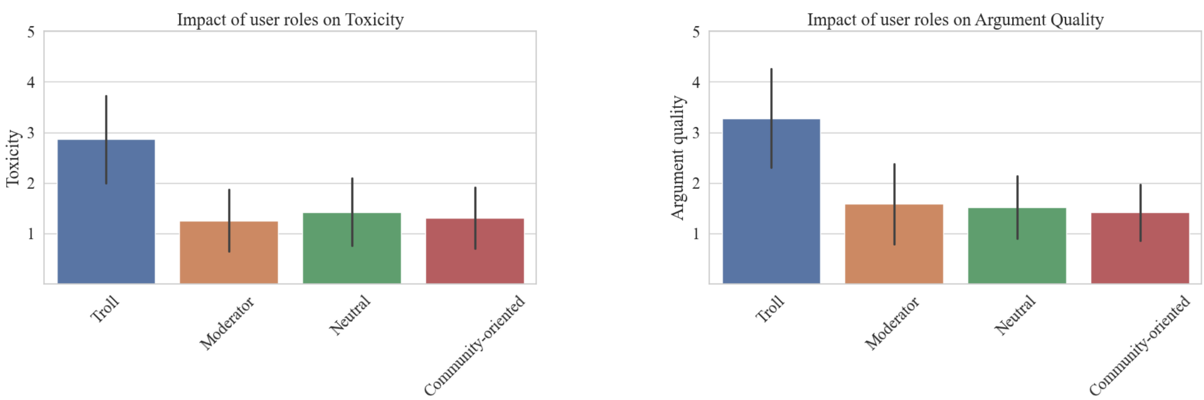

Figure 11: Average Toxicity (left) and Argument Quality (AQ) (right) per LLM user-role (§3.3).

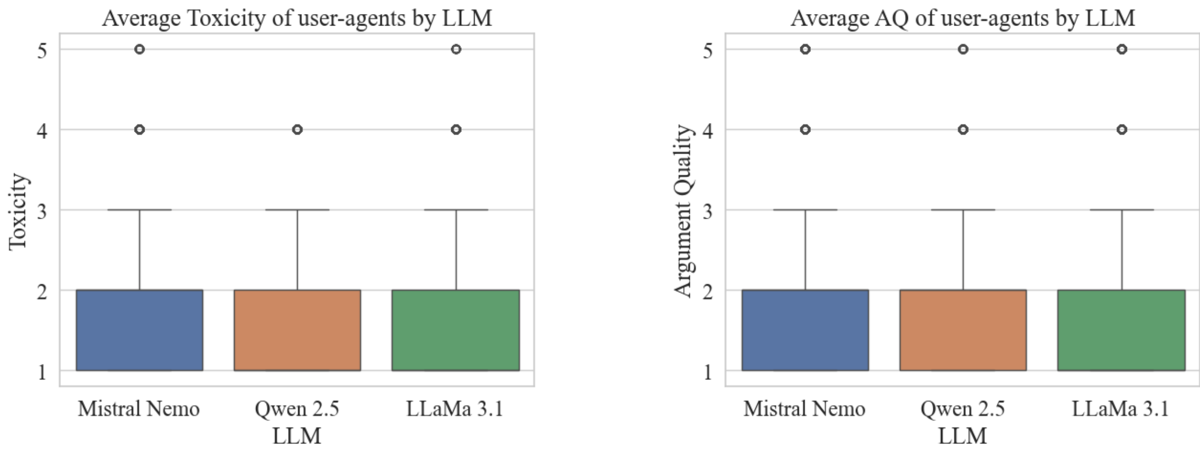

Figure 12: Boxplots for average Toxicity (left) and Argument Quality (AQ) (right) per LLM (§4.3).

- 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 Moderator Prompts

- **No Strategy**: 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

- **Collective Constitution**: 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.

- **eRulemaking**: 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.