Scalable Evaluation of Online Facilitation Strategies via Synthetic Simulation of Discussions

Anonymous 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 design principles based on existing methodologies for synthetic discussion generation. Based on these principles, we propose a simple, generalizable, LLM-driven methodology to prototype the development of LLM facilitators by generating synthetic data without human involvement, and which surpasses current baselines. 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. In an effort to aid research in the field of facilitation, we release a large, publicly available dataset containing LLM-generated and LLM-annotated discussions using multiple open-source models. This dataset can be used for LLM facilitator finetuning as well as behavioral analysis of current out-of-the-box LLMs in the task. We also release an open-source python framework that efficiently implements our methodology at great scale.

Framework —
https://anonymous.4open.science/r/framework-850F

Replication Code —
https://anonymous.4open.science/r/experiments-F54D

Dataset —
https://anonymous.4open.science/r/experiments-F54D/data/datasets/main/main.zip

1 Introduction

The modern social media environment has evolved to be extremely demanding, with users facing ever-increasing threats such as targeted misinformation (Clemons, Schreieck, and Waran 2025; Denniss and Lindberg 2025), hate speech (Kolluri, Murthy, and Vinton 2025), and polarization (Pranesh and Gupta 2024). These threats can cause serious emotional and mental harm (Schluger et al. 2022), radicalization (Cho et al. 2024), real-world violence (Schaffner et al. 2024), as well as sabotage democratic dialogue (Esau, Friess, and Eilders 2017; Falk et al. 2021; Seering 2020), trust in democratic institutions (Schroeder, Roy, and Kabbara 2024) and quality of information (Amaury and Stefano 2022). Platform designers and researchers traditionally focused on flagging and removing problematic content ("content moderation"—Seering (2020); Cresci, Trujillo, and Fagni (2022)), but these methods are no longer sufficient in practice (Horta Ribeiro, Cheng, and West 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, Trujillo, and Fagni 2022; Amaury and Stefano 2022), as well as supporting community deliberation and group decision-making (Kim et al. 2021; Seering 2020).

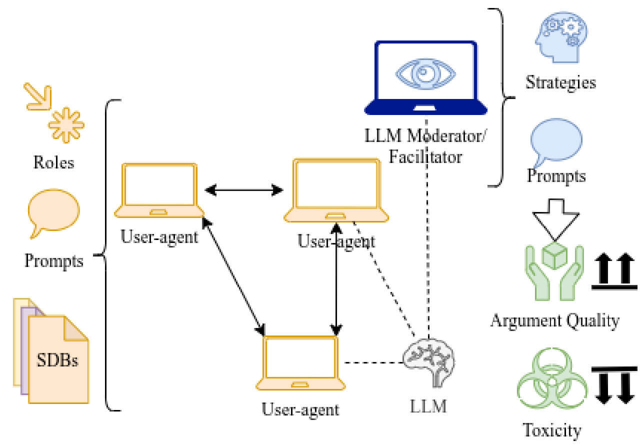


Figure 1: LLM user-agents with distinct SocioDemographic Backgrounds (SDBs—see §3.2) participate in a discussion, while the LLM moderator monitors and attempts to improve the quality of the discussion. We need to design prompts and configurations for both types of LLM agents.

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), making them a viable choice for modern large-scale social networks. However, experimentation and development on these systems is hampered due to the costs of human participation—in this case, human discussants and evaluators (Rossi, Harrison, and Shklovski 2024). 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, Harrison, and Shklovski 2024), before testing them with human participants.

Our work asks the following RQ: *How do we design and evaluate Synthetic Discussion Generation (SDG) methodologies satisfying registered criteria*? To answer this question we draw examples from methodologies proposed in literature, to establish basic design principles (§3.1), and propose a methodology enabling rapid model "debugging" (e.g., discarding suboptimal LLM prompts) and testing without human involvement (Fig. 1, §3.2). We validate the outcome through an ablation study (§5.2). To show the impact of our approach, we implement a framework based on the proposed methodology, which allows the design and evaluation of facilitation strategies proposed in modern Social Science research. We then investigate how they can enhance the performance of LLM facilitators and compare them with two common facilitation setups (§4.2) and find that while the presence of LLM facilitators has a *positive, statistically significant* influence on the quality of synthetic discussions, facilitation strategies inspired by Social Science research often *do not outperform simpler strategies* (§5.1). We also discover previously unreported aberrant behavior on the part of the LLM facilitator, in the form of excessive policing.

Finally, we release an open-source Python framework, available via PIP, that implements our methodology at scale, enabling the research community to rapidly experiment with LLM-based facilitators. Given that existing facilitation datasets are few and generally small (Korre et al. 2025), we also release 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 analyzing the behavior of out-of-the-box LLMs in the task of online facilitation. We use open-source LLMs and include all relevant configurations in order to make our study as reproducible as possible.

2 Background and Related Work

2.1 Synthetic Discussions

While studies exist for simulating user interactions in social media (Park et al. 2022; Mou, Wei, and Huang 2024; Törnberg et al. 2023; Rossetti 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) extract topics and comments from online human discussions and prompt an LLM to continue them. However, they do not use LLM-based user agents to simulate conversational dynamics, nor do they include facilitators in their setup. Additionally, their approach depends on the availability of human discussion datasets with the desired topics. Ulmer et al. (2024) create synthetic discussions between two roles: an agent controlling a fictional environment and a client interacting with it. These discussions are filtered and used to finetune the agent LLM for a specific task. Our methodology generalizes their framework: an agent (facilitator) interacts with multiple clients (non-facilitator users). Finally, Abdelnabi et al. (2024) generate synthetic negotiations involving multiple agents with different agendas and responsibilities. Our work can be seen as a domain shift of their approach—from negotiation to discussion facilitation—where various user types (e.g., normal users, trolls, community veterans) engage in discussion overseen by a facilitator with veto power.

2.2 LLM Facilitation

Unlike classification models traditionally used in online platforms, LLMs can actively facilitate discussions (Korre et al. 2025). They can warn users for rule violations (Kumar, AbuHashem, and Durumeric 2024), monitor engagement (Schroeder, Roy, and Kabbara 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, Niella, and Garbulsky 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 high-quality feedback to users, although they struggle to make users more respectful and cooperative. In contrast to both works, ours uses exclusively LLM participants and LLM facilitators, and tests the latter in an explicitly toxic and challenging environment.

2.3 Discussion Quality

We need to evaluate two different quality dimensions. One is *discussion quality as seen by humans*, which is difficult to measure, both because of the breadth of the possible goals of a discussion, and because of the lack of established computational metrics in Social Science literature (Korre et al. 2025). There are however some that could reasonably be applied in this domain, such as toxicity (De Kock, Stafford, and Vlachos 2022; Xia et al. 2020), connective language (Lukito et al. 2024) and political discussion quality (Jaidka 2022).

The second quality dimension is measuring "high-quality" or "useful" data. This is essential in LLM-based discussion frameworks, as such discussions tend to deteriorate quickly without human involvement, often becoming repetitive and low-quality (Ulmer et al. 2024). Despite this importance, methods for quantifying the quality of synthetic data remain limited.

Balog et al. (2024) use a mix of graph-based, methodology-specific, and lexical similarity metrics, many of which depend on human discussion datasets. Their most generalizable measure is a loosely defined "coherence" score, which is LLM-annotated without theoretical grounding. Kim et al. (2021) assess quality through post-discussion surveys and by measuring lexical diversity to approximate the variety of opinions expressed. Ulmer et al. (2024) introduce a discussion-level metric called *"Diversity"*, which penalizes repeated text sequences between comments using average pairwise ROUGE-L (Lin 2004) scores. Their approach suffers from the limitations of ROUGE scores (mainly the use of exact-word matching), but their metric is computationally efficient, explainable and independent from any specific domain and dataset.

2.4 LLMs as Human Subjects

While there is always a desire for synthetic simulation systems to be "realistic" w.r.t. human behavior (Grossmann et al. 2023; Törnberg et al. 2023; Argyle et al. 2023), this can not be claimed nor reliably measured by using LLM agents in lieu of humans (Rossi, Harrison, and Shklovski 2024).

It is true that LLMs have demonstrated complex, emergent social behaviors (Park et al. 2023a; Marzo, Pietronero, and Garcia 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, Harrison, and Shklovski 2024); sociodemographic, statistical and political biases (Anthis et al. 2025; Hewitt et al. 2024; Rossi, Harrison, and Shklovski 2024; Taubenfeld et al. 2024); unreliable annotations (Jansen, gyo Jung, and Salminen 2023; Bisbee et al. 2024; Neumann, De-Arteaga, and Fazelpour 2025; Gligori'c et al. 2024); non-deterministic outputs (Atil et al. 2025; Bisbee et al. 2024); and excessive agreeableness (Park et al. 2023b; Anthis et al. 2025; Rossi, Harrison, and Shklovski 2024).

Thus, *no study based on LLM agents* can claim that it generates"realistic" discussions; reproduction studies with humans are ultimately needed.

3 Methodology

3.1 Designing synthetic discussions

Many SDG frameworks have been proposed in literature; both simple (Tsai, Qian, and comm. contributors 2025; Ulmer et al. 2024) and complex (Balog et al. 2024; Abdelnabi et al. 2024; Park et al. 2023a). Concordia (Vezhnevets et al. 2023) is an example of a general, complex framework—while impressive from a technical standpoint, it has failed to garner widespread adoption despite efforts to promote it, as evidenced by most recent publications creating their own SDG frameworks. What makes such a framework widely used (perhaps modified) by other people has not been explored in literature, despite many such implementations.

In the field of Software Engineering, there is a widely shared notion that simple systems are almost always better at performing their functions ("Keep It Simple Stupid"—KISS) (Beck 2000; Thomas 2025), which has been validated in real life (Banker and Datar 1989; Ogheneovo et al. 2014). Following this notion, we establish our first design rule: *(1) The framework must be as simple as possible*. The violation of this simple rule could explain the under-performance of Concordia or the frustrations of Balog et al. (2024). A natural extension of this rule is *(2) When we do need to add complexity, this needs to be justified both epistemologically and quantitatively*. Indeed, each contribution of our methodology is evaluated before being adopted (§5.2). From our experiments, we also encountered a new limitation: *(3) Complexity is directly related to researcher bias*; each new feature necessarily follows our own expectations with how human discussions work. The work of Park et al. (2023a) managed to derive interesting insights, exactly because it did *not* tamper with the way LLM users interacted.

With regard to functionality, we posit that synthetic discussion methodologies need to at least implement the following components: *(1) Context management*—since LLMs are stateless, and need to be fed information as prompts, *(2) Turn-taking*—as LLMs are trained as chatbot assistants, and therefore can not decide *not* to speak, *(3) Instructions given to the LLMs*—which may need to be diversified in multi-participant discussions.

3.2 Our methodology

Context Management We assume that the h most recent comments provide sufficient context for the LLM users, facilitators, and annotators; a technique that works well in the context of discussions (Pavlopoulos et al. 2020). While techniques such as dynamic summarization (Balog et al. 2024), LLM self-critique (Yu et al. 2024), or memory modules (Vezhnevets et al. 2023) exist, they result in greater computational cost and a less transparent and explainable system.

Turn Taking In online fora users often create "comment chains" following-up on responses to their previous comments. Thus, for each discussion turn we either allow the previous user to respond (with a 40% probability), or select another random participant (60%). This probability was selected experimentally; larger values tend to create "debate"-style discussions between only two or three participants, while lower values tend to create scenarios with minimal interaction between them.[1] A facilitator can respond after every comment, or stay silent by emitting an empty string.

Instruction Prompting We use a standard instruction prompt for the participants instructing them to respond to repeatedly toxic comments. This was a necessary measure to bypass the extreme agreeableness of LLMs (as seen in §5.2 and in literature—Park et al. (2023a); Anthis et al. (2025)) and is an example of the trade-off between complexity and research bias v.s. the need to acquire meaningful data. Facilitators are instructed to respond only when necessary.

Following the paradigm presented by Abdelnabi et al. (2024), we assign roles to non-facilitator participants (e.g., helping the community or disrupting discussions). We create three roles with distinct instructions for users (see supp. material): neutral users, trolls, and community veterans. We

[1]It would be interesting to analyze quantitatively how discussions change when modifying this parameter, but this is outside of the scope of our work.

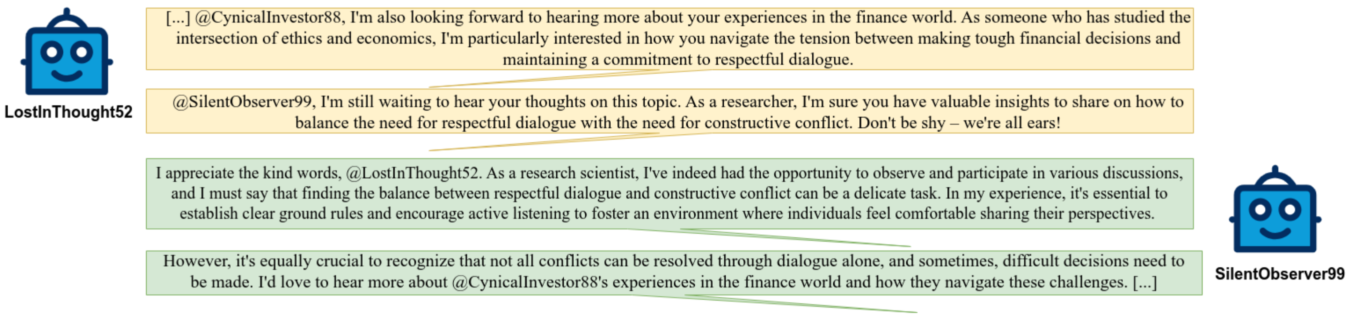


Figure 2: Excerpt from a synthetic discussion. The LLM participants use their sociodemographic prompts to insert personal stories and justify their perspectives in the discussion. They are also able to learn and retain information about other agents through conversation (a behavior also observed in Park et al. (2023a)). User `CynicalInvestor88` is also a part of the discussion; not a hallucination. Comments clipped due to length.

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

Table 1: Sociodemographic information provided to the LLM participants and annotators. We defer the reader to the supplementary material for the actual values.

verify that roles have a quantitative effect on the toxicity of participants in §5.2.

LLM Personas Including SocioDemographic Backgrounds (SDBs—information such as gender, age and education) in prompts has proven promising in the generation of varied content and alleviation of Western bias exhibited by them (Burton et al. 2024). We generate 30 LLM user personas with unique SDBs (Table 1) by prompting a GPT-4 model (OpenAI 2024). Using these sociodemographic prompts, we observe that LLM users are able to create and share personal narratives and experiences from the provided information (Fig. 2).

4 Experimental Setup

4.1 Synthetic Discussion Generation

We use a set of starting comments ("seed opinions")—in our case controversial statements from Pavlopoulos and Likas (2024). We then run $N_d = 8$ discussions for each pair of facilitation strategies S and LLM (§4.4). An overview of how the experiments are generated can be found in Algorithm 1. The $RandomSample$ function returns a number of samples from a set following the uniform distribution. The $Actors$ function creates a LLM agent using a model and a prompt.

Algorithm 1: Synthetic discussion setup generation

Input:
- User SDBs $\Theta = \{\theta_1, \ldots, \theta_{30}\}$
- Strategies $S = \{s_1, \ldots, s_6\}$
- Seed opinions $O = \{o_1, \ldots, o_7\}$
- LLMs = $\{LLaMa, Mistral, Qwen\}$

Output: Set of discussions D

```
D = {}
for llm ∈ LLMs do
    for s ∈ S do
        for i = 1, 2, ..., N_d do
            Θ̂ = RandomSample(Θ, num = 7)
            U = Actors(llm, Θ̂)
            m = Actors(llm, s)
            o = RandomSample(O, num = 1)
            d = {users: U, mod: m, topic: o}
            D = D ∪ d
return D
```

4.2 Facilitation Strategies

We test four different facilitation strategies, three of which are derived from Social Science research, along with two common-place strategies for discussion facilitation. Note that the process of turning sometimes extensive documents into short prompts, necessitated by open-source LLMs, is necessarily imperfect. We leave the optimal derivation of strategy prompts to future work.

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. This approach is already being used in some platforms (Tsai, Qian, and comm. contributors 2025). Example: "You are a moderator, keep the discussion civil".
3. **Rules Only**: A *real-life* strategy where the prompt is adapted from LLM alignment guidelines (Huang et al. 2024). These guidelines were selected to be as unanimously agreed upon as possible across various human groups. They thus provide a set of rules to uphold, without specifying *how* to uphold them, leaving the LLM

completely unconstrained. Example: “Be fair and impartial, assist users, don’t spread misinformation”.

4. **Regulation Room**: A *real-life* strategy based on guidelines given to human facilitators of the “Regulation Room” platform (eRulemaking Initiative 2017). The instructions are suitable for online fora, where facilitators also engage in content moderation, and their effectiveness must be balanced by their throughput. Example: “Stick to a maximum of two questions, use simple and clear language, deal with off-topic comments”.
5. **Constructive Communications**: A *real-life* strategy based on the human facilitation guidelines used by the MIT Center for Constructive Communications (White, Hunter, and Greaves 2024). It approaches facilitation from a more personalized and indirect angle, forbidding facilitators from directly providing opinions or directions. This makes the strategy ideal for deliberative environments. Example: “Do not make decisions, be a guide, provide explanations”.
6. **Moderation Game**: Our proposed *experimental* strategy, inspired by Abdelnabi et al. (2024) (see §2.1). Instructions are formulated as a game, where the facilitator LLM 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 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”.[2]

4.3 Evaluation

We use *toxicity* as a proxy for discussion quality, since it can inhibit online and deliberative discussions (De Kock, Stafford, and Vlachos 2022; Xia et al. 2020)[3]. We use ten LLM annotator-agents controlled by a model already used in prior work—LLaMa3.1 70B (Kang and Qian 2024)—as LLMs are reliable for toxicity detection (Wang and Chang 2022; Anjum and Katarya 2024). Having controlled for inherent model variance and bias (by using multiple SDB prompted LLM runs as in §3.2), the use of a reliable LLM metric means we avoid circular validation issues.

In order to gauge the quality of our synthetic discussions, since we can not reliably measure “realism” (§2.4), we use the “diversity” metric (Ulmer et al. 2024). 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). We 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.

We note again that these metrics are better interpreted as heuristics of actual discussion and synthetic data quality respectively. More research is needed w.r.t. reliable and generalizable quality metrics.

4.4 Technical Details

We use three instruction-tuned, open-source models: LLaMa3.1 (70B), Qwen2.5 (33B), Mistral Nemo (12B), quantized to 4 bits and run using a set seed (42). All the experiments were collectively completed within four weeks of computational time, using two Quadro RTX 6000 GPUs. The execution script is available in the project’s repository.

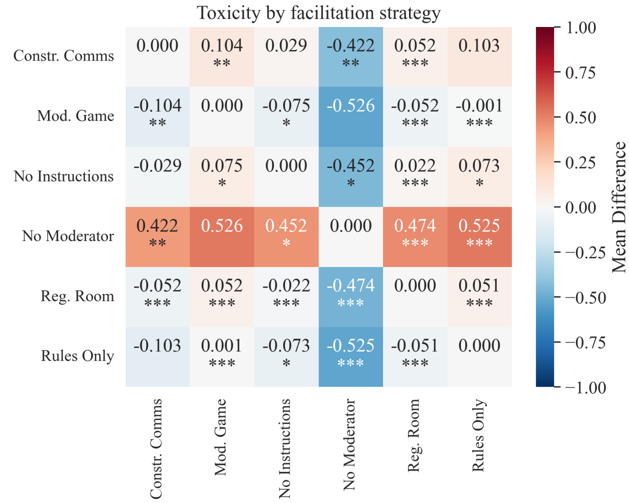


Figure 3: Difference in average toxicity levels for comments following pairs of facilitation strategies. Red cells ($x > 0$) indicate that the strategy on the left performs worse than the one on the bottom, for an average of x points in a scale of 1-5. Conversely for blue ($x < 0$) cells. White cells denote minute changes. Asterisks derived from pairwise Student-t tests ($\cdot p < 0.1$, $^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$). The large size of our dataset allows using parametric tests.

5 Results

5.1 Main findings

Finding 1: LLM facilitators significantly improve synthetic discussions over time. Unmoderated discussions tend to display significantly higher levels of toxicity (Fig. 3, Table 2). A linear regression analysis of toxicity over time ($Adj.R^2 = 0.413$) reveals that trolls exhibit intense toxicity—on average 1.3288 points above neutral users and 1.3112 above community veterans ($p < .000$) which decreases by an average of -0.0125 points per turn ($p = 0.003$). This trend is even more pronounced for neutral participants and community veterans, whose toxicity drops by -0.0225 ($p < .000$) and -0.0350 ($p < .000$) points per turn, respectively. This demonstrates the ability of the facilitator to reign in discussions over time, but also the diverging behaviors of different roles.

[2]This could serve as a basis for a similar methodology based on game-theory, or as a Reinforcement Learning formulation for training. In this work we only explore whether the prompt itself can have an effect on the LLM facilitator; we leave the aforementioned approaches for future work.

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

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 2: OLS regression coefficients for toxicity on the non-facilitator comments ($Adj.R^2 = 0.054$). Reference factor is *No Moderator*. All strategies outperform *No Moderator* in general. The *Regulation Room* and *Constructive Communications* real-life strategies additionally show improvements over time compared to *No Instructions*.

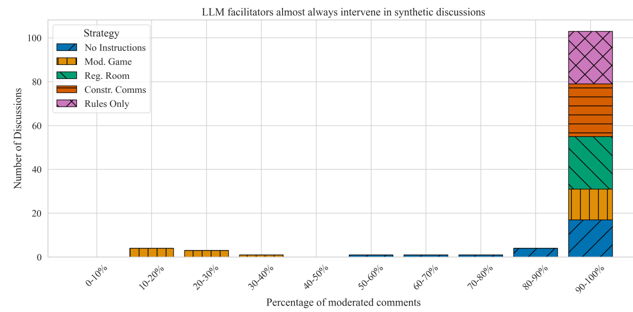


Figure 4: Histogram of interventions by LLM facilitators per strategy used.

Finding 2: Elaborate facilitation strategies fail to decrease toxicity. The real-life strategies and our own strategy (§4.2) show a slight edge over time compared to *No Instructions*, but they do not consistently outperform it (Fig 3). This suggests that out-of-the-box LLMs may struggle to meaningfully incorporate complex instructions—which has been noted in prior work (Cho et al. 2024).

Finding 3: LLM facilitators choose to intervene far too frequently, which is tolerated by the other participants. Fig. 4 demonstrates that LLM facilitators intervene at almost any opportunity, even though they are instructed to only do so when necessary. This confirms that LLMs generally can not decide not to speak even when instructed to do so (§3.2). To our knowledge, this has not been reported in relevant literature, and *is an example of "debugging" problems with LLMs* — a core motivation of our work.

Additionally, we note 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, Trujillo, and Fagni 2022). This is likely another artifact of LLMs being too agreeable (Park et al. 2023a; Anthis et al. 2025).

5.2 Ablation Study

We generate eight synthetic discussions per ablation experiment, using a single model (Qwen 2.5). We compare the diversity (cf. §2.3, §4.3) of these discussions with our broader synthetic dataset, as well as the CeRI "Regulation Room" dataset.[4] We pick this dataset because it is publicly available and comprised of facilitated online human discussions on ten diverse topics.

Each component of our methodology surpasses baselines in data quality. 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 although all distributions diverge from the blue—human—distribution, our function is the only one not exhibiting extremely high diversity (i.e., very limited participant interaction §4.3). Fig. 5c illustrates that each individual prompting design decision (SDBs, roles, and instruction prompts) results in diversity scores more closely aligned with human discussions.

Larger models do not increase the quality of discussions. 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. It's worth noting that none of the models closely matched the diversity observed in human discussions.

Specialized instruction prompts are essential for eliciting toxic behavior in instruction-tuned LLMs. Inserting trolls to the discussion, leads to more intense toxicity among *other* participants *only if we instruct them to react to toxic posts* (Fig. 6).

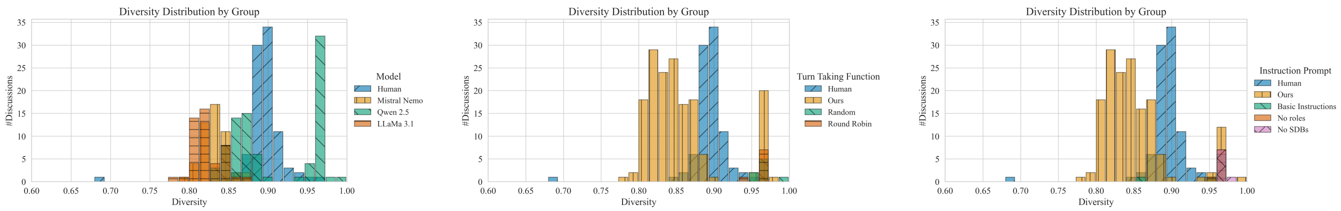
6 Datasets and Software

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

- 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.
- Availability via PIP.

We also release a dataset of synthetic discussions annotated by LLMs. It can serve for finetuning facilitator LLMs. We note that, as is the case with most synthetic

[4] 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.



(a) Model (b) Turn-taking function (c) Instruction prompt

Figure 5: Diversity (§2.3) distribution for each discussion by LLM (§4.4), turn-taking function t, and prompting function ϕ used (§3.2). Comparison with the CeRI Regulation Room dataset ("Human"). Note that the x-axis starts from 0.6.

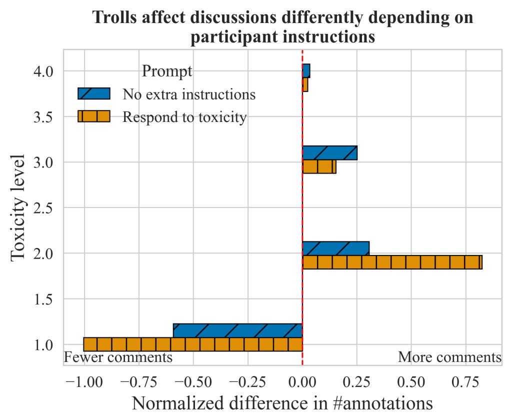


Figure 6: Non-troll toxicity levels in discussions with and without trolls. There is a significant uptick on the number of "somewhat toxic" ($Toxicity = 2$) comments when the participants are instructed to respond to toxic comments.

datasets (Ulmer et al. 2024), the data may need to be filtered to derive only high-quality samples—in our case filtering out discussions with constant facilitator interventions or low/extremely high diversity. However, the data can be scaled accordingly, due to the low computational cost of our methodology. 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. The dataset is licensed under a CC BY-SA license, and the software under GPLv3. **Warning: The datasets by their nature contain offensive and hateful speech.**

7 Conclusion

We conducted a brief overview of the tradeoff between complexity and efficiency for synthetic discussion methodologies, from which we derived three simple design rules. Following these rules, we proposed a simple and generalizable methodology, whose components are easily validated and which enables researchers to quickly and inexpensively conduct pilot facilitation experiments using exclusively LLMs. We found that LLM facilitators significantly improve the quality of synthetic discussions; but prompting these facilitators with strategies based on Social Science research does not markedly improve their performance. We also discovered that LLM facilitators constantly intervene, even when instructed not to. Finally, we created an open-source Python Framework that applies this methodology to hundreds of experiments, and which we used to create and publish a large-scale synthetic dataset, which can be used for finetuning.

8 Discussion

Future work Future work should identify additional quality metrics to evaluate synthetic data, and discussion quality. The latter can then be used to examine the applicability of our findings obtained regarding optimal facilitation strategies, to discussions involving humans. It would also be interesting to explore how to more effectively prompt LLMs with complex facilitation strategies, or alternative formulations of our methodology, as described in this paper.

Limitations Given the limited prior research our methodology is mostly exploratory, and is evaluated with baselines using only two metrics. Our setup is restricted by the statelessness of LLMs, which forces us to overwhelmingly resort to prompting—however the use of open-source models prevented us from experimenting with more elaborate prompts requiring extended context windows.

Ethical considerations Synthetic discussions involving LLMs could be exploited by malicious actors to train them at performing unethical tasks (Majumdar et al. 2024; Marulli, Paganini, and Lancellotti 2024; Li et al. 2025), although ongoing research is addressing these vulnerabilities (Wang et al. 2025). Furthermore, the use of LLMs inherently risks skewing moderation systems towards the predominant demographics best represented in their training data. SDB prompts are a necessary but insufficient step towards avoiding this (Rossi, Harrison, and Shklovski 2024; Anthis et al. 2025; Burton et al. 2024).

AI use statement LLMs were used solely for styling and text corrections in this document. They were also partially used for generating framework documentation, and to generate code for some of the presented graphs. All such changes and additions have been checked by the authors.

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