This House Debates AI: Evaluating a Language Model in Oxford-Style Debates Against Human Experts

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Abstract

Recent work shows that large language models (LLMs) are increasingly capable of generating persuasive arguments and messages, creating concerns over undue influence on human beliefs. Most evidence so far, however, evaluates LLM argumentation and persuasion in single-turn interactions and/or compares to weak human baselines. To address this gap, we benchmark a state-of-the-art LLM, Llama 3.1 Instruct 405B, in 100 six-turn Oxford-style debates against 20 experienced human debaters. Each anonymised debate is rated by 5 independent raters, who provide win/loss judgments as well as 0–100 scores across 11 dimensions of quality. Based on these ratings, the LLM is competitive overall, with a win rate of 51.2%, ranking 6th out of 21 debaters on mean performance score. Compared to humans, the LLM generally scores higher on presentational dimensions (e.g., clarity, confidence, formality) but equal on most substantive dimensions (convincingness, evidence, originality). We also find that pre/post rater stance tends to shift towards the position raters chose as the winning side, regardless of whether this side was the LLM or a human. Overall, our results provide new evidence on the qualities of LLM argumentation and its drivers, suggesting strong argumentative competence even in competitive multi-turn settings.

1. Introduction

Current large language models (LLMs) can generate highly persuasive texts, often as well or better than human experts [Hackenburg et al., 2025a]. Future, more capable models, using advanced post-training methods, are likely to be even more persuasive [Hackenburg et al., 2025b]. This trend bolsters concerns that malicious actors may use LLMs to influence public opinion and undermine the integrity of democratic discourse [Buchanan et al., 2021, Goldstein and Sastry, 2023].

To meet these concerns, a growing body of work seeks to measure the persuasiveness of LLMs across different settings and political issues. Most studies so far, however, conduct *single-turn* evaluations where LLMs write messages or arguments that are then shown to human participants [e.g. Durmus et al., 2024, Goldstein et al., 2024, Hackenburg and Margetts, 2024, Hackenburg et al., 2025c]. Persuasion and argumentation in *multi-turn* settings, which require more sustained argumentative competence, are studied primarily in non-competitive settings [Costello et al., 2024, Liu et al., 2024, Salvi et al., 2025, Hackenburg et al., 2025b] and often marred by issues of automated evaluation and/or comparison to weak human baselines.

We address this gap by benchmarking a state-of-the-art LLM (Llama 3.1–Instruct 405B) in multi-turn Oxford-style debates against human experts. We collect 100 structured debates between the LLM and 20 expert debaters. Following the established Oxford debate style [Eckstein and Llano, 2017], each debate on a given motion (e.g., "This House Would Make Voting Compulsory") consists of Opening, Rebuttal, and Closing turns from both Proposition and Opposition sides, which we randomly assign between the LLM and humans. For each debate, at least five independent raters, blind to one side being an LLM, cast a win/loss vote and provide 0–100 scores on eleven dimensions of argument quality. We then use this rich multi-turn data to answer three key research questions:

RQ1 (Performance Comparison). How does a state-of-the-art LLM perform against expert humans in multi-turn Oxford-style debates?

We find that the LLM is competitive overall, with a win rate of 51.2% against the expert debaters, ranking sixth out of 21 debaters based on mean performance score. The LLM generally scores significantly higher than humans on presentational dimensions of argument quality (e.g., Clarity, Confidence, Formality) while showing no significant difference on most substantive dimensions (Convincingness, Evidence, Originality).

RQ2 (Predictors of Winner Choice). Which perceived quality dimensions are most strongly associated with the raters' blinded winner choice?

We find that winner choice is most strongly associated with the more substantive dimensions of argument quality, i.e., exactly those dimensions that the LLM tends to not outperform humans on. Relative advantages in Convincingness, Issue Knowl-

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edge, and Engagingness predict victory, whereas advantages on Clarity and Formality do not.

RQ3 (Rater Stance Change). Does engaging with the debates change rater issue stance, and, if so, does the magnitude of this change depend on debater identity (LLM or human)?

We find a significant shift in rater stance on the debate motions which tends towards the side judged as the winning side by the rater. Whether the chosen winner is an LLM or human, on the other hand, is not significantly associated with observed stance change, although we note that this warrants further validation in a larger-scale study.

Overall, we make **four main contributions**:

1. We formalize a reproducible protocol for evaluating LLMs in multi-turn debate: a fixed six-turn, text-only Oxford format with 100–150 words per turn, anonymized A/B transcripts and double-blinded human judging, as well as an eleven-dimension rating rubric.

2. We provide the first ever head-to-head assessment of a state-of-the-art LLM in such multi-turn Oxford-style debates against expert human debaters, showing that the LLM performs competitively overall and across several granular dimensions of argument quality.

3. We show that argument substance better predicts winner choice than presentational advantages, and that rater stance change tends to follow the chosen winner, not debater identity.

4. We make all prompts, rater materials, and our study interface available in our code repository to enable replication of our evaluation protocol and benchmarking of future LLM releases.

2. Experimental Setup

2.1. Debate Format

We adopt a text-only Oxford-style debate format, where two sides (Proposition and Opposition) argue about a given motion. Each debate follows a fixed six-turn sequence: Opening by Proposition and Opposition, then Rebuttal by Proposition and Opposition, then Closing by Proposition and Opposition [Eckstein and Llano, 2017]. In our experiments, we set the maximum length of each turn at 150 words for both sides, to limit the time/cost of collecting human debate contributions given our limited budget. To preserve symmetry between human debaters and the LLM, we disallow the use of external links and citations. This increases the internal validity of our comparative evaluations at limited cost to ecological validity. Human debaters are given five minutes to prepare at the beginning of each debate. In summary, instructions given to both sides are minimal and symmetric: a fixed six-turn structure, a hard cap of 150 words per turn, and no external links or citations. In every turn, we ensured that the LLM had access to the same information as human debaters (details in §2.4).

We adopt the Oxford debate format because it is widely used and easily understood by general audiences (raters), and because its symmetric, turn-based structure supports clean A/B comparisons and blinded text rating. Compared to alternatives such as policy or parliamentary formats, Oxford debates have shorter, self-contained speeches and clearer role symmetry, which are well suited to text-only collection and scalable evaluation.

2.2. Phase 1: Expert Debates

We recruited 20 expert debaters to each complete five debates against an LLM, for a total of 100 debates. All debaters were members of the Oxford Debate Society – one of the world's leading university debate clubs – and/or attended at least one of their training sessions. Accordingly, participants reported substantial prior debate experience (35% at national/international, 30% at regional, 25% at club level; 5% with professional coaching/judging experience; 5% prefer not to say) and high familiarity with the Oxford format (55% very familiar, 35% moderately familiar). The sample skewed young (80% aged 18–29 years; 20% 30–39 years), male (80% male, 20% female), and educated (15% holding A-levels, 65% undergraduate, 20% postgraduate degrees). We will share additional details on debater demographics and experience in the Appendix upon acceptance.

For each debate, we randomly assigned one of ten debate motions (Table 1) and randomly assigned sides (Proposition, Opposition), such that i) each debate motion was debated ten times and ii) humans and the LLM were each assigned each side equally often. We collected debates using a custom web interface. Each debater received a £20 gift card after completing five full debates.

2.3. Phase 2: Rating

For *in-person* Oxford-style debates, winners are typically determined by audience vote shifts between pre- and post-debate ballots. To enable efficient evaluation in our text-only online setting, we recruited 61 UK-based raters through Prolific. Prior exposure to formal debate was limited among raters (83.6% non/some, 16.4% moderate/extensive). For additional rater demographics, see Appendix B.

Raters each provided ratings for ten debate transcripts from Phase 1, for which they were compen-

Theme	Motion
Technology & Society	• This House Would Ban Facial Recognition Technology in All Public Spaces • This House Regrets the Rise of AI-Generated Art
Environment & Sustainability	• This House Would Ban Single-Use Plastics Entirely • This House Believes Nuclear Energy Is Essential to Achieve Net Zero
Work	• This House Regrets the Rise of Remote Work • This House Would Mandate a Four-Day Workweek
Media & Culture	• This House Regrets the Rise of Dating Apps • This House Regrets the Proliferation of Reality Television
Governance & Democracy	• This House Would Make Voting Compulsory • This House Would Ban Targeted Political Advertising Online

Table 1: **Debate motions** used in our experiments. From the catalogue of real motions debated at the Oxford Union during the 2024/25 academic year, we select two motions across each of five themes.

sated at a rate of around £10 per hour.[1] All ratings were collected under strict blinded conditions: Debaters were shown as "Debater A/B", debater self-references were removed from debate transcripts, and raters were not told about the study's full aims or that one side could be an LLM.

For each transcript, we ask raters to make a binary choice of the overall winner. Also, for each side of the debate, we ask raters to provide 0–100 ratings for overall performance as well as ten granular dimensions of argument quality. When discussing results throughout the paper, we split these dimensions into *presentational* attributes (Clarity, Confidence, Formality) versus *substantive* attributes (Knowledge, Logic, Evidence, Convincingness, Originality, Engagingness, Rebuttal).

Additionally, before reading each transcript, raters indicated their stance on the motion on a 0–100 scale, where 0 indicated strong disagreement and 100 indicated strong agreement with the Proposition. After completing all ratings for a transcript, raters were asked to indicate their stance on the same scale again. The difference between these two responses constitutes our measure of stance change, which we use to answer RQ3.

Overall, we collect 522 complete sets of ratings (rater x debate transcript pairs), with each debate transcript receiving at least five ratings.

2.4. LLM and Inference Setup

In principle, any LLM could be pitted against human debaters and assessed using our evaluation protocol. Due to budget constraints, we only evaluate a single LLM in this study. We choose the 405B parameter version of Llama 3.1 Instruct [Manchanda et al., 2024] because i) the open-weight release of the model maximises reproducibility and transparency, ii) the model is generally strong on reasoning and knowledge tasks [Grattafiori et al., 2024] and iii) particularly strong at generating persuasive texts [Hackenburg et al., 2025a]. Further, the model's 32k-token context window comfortably fits each six-turn transcript in our setting.

We collect model responses via the OpenRouter API, using provider defaults for all sampling parameters as well as a maximum token count of 4,000, which in practice was never reached. To frame the debate task, we provide the model with a single fixed system prompt as well as three turn-specific prompt templates (Opening, Rebuttal, Closing). At each turn, the model is shown the motion, the side it is assigned to argue for (Proposition or Opposition), and, when applicable, the opponent's prior turns, thus matching the information available to human debaters. For exact prompts, sampling parameters, and interface screenshots see our code repository.

3. Experiments

3.1. RQ1: Performance Comparison

First, we evaluate the overall debate performance of the LLM compared to human debaters. For this purpose, we measure win rates and mean performance scores for the LLM and human debaters provided by independent raters (Figure 1).

Win Rate Raters judged the LLM to be the winner in 267 out of 522 rater-debate pairs, corresponding to an overall win rate of 51.15%. This places the LLM 10th out of the 21 debaters. Win rates vary substantially across human debaters. Rater agreement on who won a given debate, measured by Krippendorff's α, was 0.078. Average raw agreement was 71.8%.[2] Both measures indicate agreement marginally above chance, suggesting that winner choice is a highly subjective task.

[1] Actual compensation for each rater varied depending on how quickly they completed the rating task.

[2] The minimum possible in our binary setup is 50%.

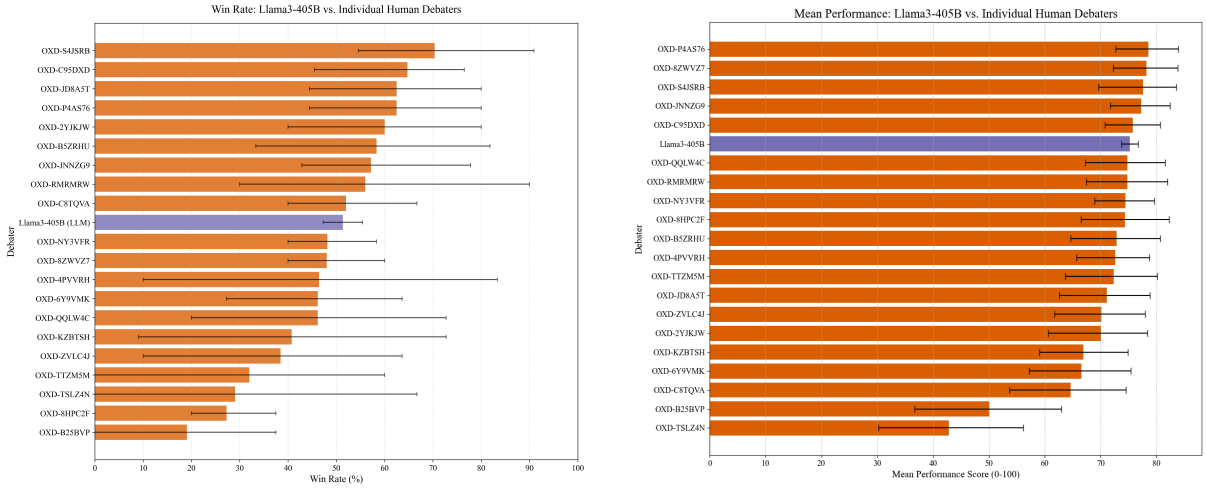


Figure 1: **Overall debate performance** of the LLM (blue) versus human debaters (orange) as judged by independent blinded raters. **[left]**: debater-level win rate, where the LLM places 10th out of 21 debaters. **[right]**: mean debater-level performance score (0-100 scale), where the LLM places 6th out of 21 debaters. All bars show 10,000-sample 95% bootstrapped confidence intervals.

Overall Performance Score The LLM received an average of 75.25 points on a 0-100 scale, which places it 6th out of the 21 debaters.[3] This placement appears to be explained in part by variation in the expertise of the human debaters, which we show by comparing the LLM to humans grouped by self-reported expertise level. Table 2 reports group statistics and cluster-robust pairwise comparisons with 10,000-sample bootstrap 95% CIs. We find that the LLM's mean performance score (75.2) is significantly higher than that of Low (67.7; diff = +7.56, p=0.003) and Medium expertise debaters (69.2; diff = +6.07, p=0.006), but not significantly different from that of High expertise debaters (72.7; diff = +2.52, p=0.136). This indicates the LLM clearly outperforms less-experienced debaters while performing roughly on par with the most experienced group.

Difference in Granular Quality Ratings Next, we analyse more fine-grained differences in LLM- and human-written debate content. For this purpose, we make within-rater, same-debate comparisons across the ten granular dimensions of argument quality introduced in §2.3. Table 3 reports mean scores for both sides on the ten attributes (0–100) and paired t-tests for significance of differences with Holm–Bonferroni correction.

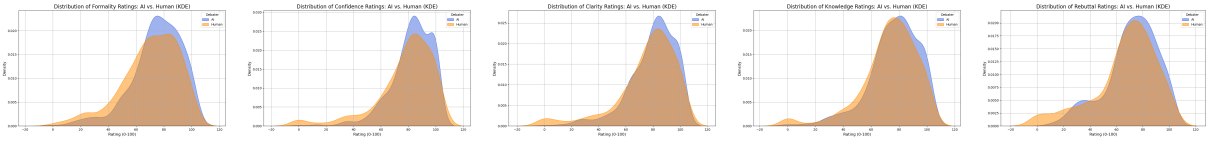
Overall, we find significant LLM advantages on five of the ten attributes. These gains are strongest on *presentational* attributes – Formality ($\Delta = +5.10$, p<.001), Confidence ($\Delta = +5.09$, p<.001), and Clarity($\Delta = +4.55$, p<.001) – and extend to two *substantive* attributes – Rebuttal Quality ($\Delta = +4.98$, p=0.001) and Issue Knowledge ($\Delta = +3.49$, p=0.011). Differences on Argument Logic, Engagingness, Convincingness, Use of Evidence, and Originality are not significant after correction. Thus, while the LLM shows advantages on both presentational and substantive dimensions of argument quality, they are particularly pronounced for presentational attributes. Notably, the LLM does not score significantly worse than human debaters on any of the ten rating attributes.

Further descriptive analysis suggests that LLM advantages are driven by greater consistency in LLM performance compared to human debaters: Figure 2 visualizes the full distribution of rater scores (0–100) for the LLM and human debaters on the ten granular attributes (excluding "Overall Performance"). Consistent with Table 3, the LLM curves are typically shifted rightward and are narrower, which indicates higher central tendency. Additionally, we find less mass in the lower tail for LLM score distributions, while human scores exhibit heavier left tails, meaning that the LLM rarely scores low on any of the rating dimensions while human debaters sometimes score very poorly.

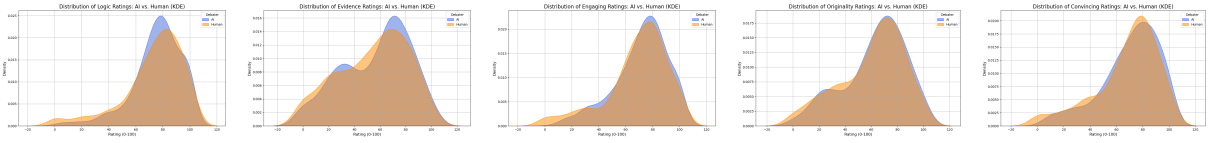
3.2. RQ2: Predictors of Winner Choice

Next, which factors are associated with winner choice. Specifically, we test which of the dimensions of argument quality that we asked raters to score best predict rater choice of the overall debate winner. For this purpose, we model the raters' binary winner choice with a logistic regression, using score differences between the two debaters as predictors. Formally, the model is specified as $\log(P(\text{win}_A)) = \beta_0 + \sum_k \beta_k \, \Delta\text{Score}_k$ for each of our k=10 granular 0-100 rating dimensions. In this model, positive coefficients indicate that a higher

[3] Rater agreement on the overall performance scale as measured by standard deviation was 17.43.



(a) Formality (b) Confidence (c) Clarity (d) Knowledge (e) Rebuttal



(f) Logic (g) Evidence (h) Engagingness (i) Originality (j) Convincingness

Figure 2: **Score distributions by rating attribute.** Kernel density estimates of rater scores (0–100) for the LLM (blue) and human debaters (orange) across ten granular dimensions of argument quality, matching Table 3. Curves share a common bandwidth and are truncated to the 0–100 range. Compared to score distributions for human debaters, score distributions for the LLM are typically shifted right and less heavy-tailed, especially on presentational attributes (Formality, Confidence, Clarity).

relative score assigned to a side by a given rater increases the odds of that rater choosing this side as the winner. The model is a strong fit for our data, as indicated by a Pseudo R^2 of 0.67, and it isolates a small set of significant attributes (Table 4).

Overall, rater winner choice is associated more strongly with substantive than presentational advantages. The strongest predictors are relative advantages in Convincingness (OR=1.06, p=0.005), Issue Knowledge (OR=1.06, p=0.002), Engagingness (OR=1.05, p=0.027), and Rebuttal Quality (OR=1.04, p=0.009), i.e. substantive dimensions of argument quality. For example, for every 1-unit increase in the difference in Convincingness as perceived by a given rater, the odds of this rater picking the more convincing debater as the winner increase by x1.06. Differences on other rating dimensions, including those related primarily to presentational quality (e.g., Clarity, Formality), are not significant predictors of rater winner choice.

Notably, most of the significant (substantive) dimensions are not the (presentational) dimensions on which LLMs tend to score higher than human debaters (§3.1). This may explain why LLMs rank lower compared to human debaters based on win rates than based on aggregate performance scores: If argument substance matters most to raters, then the presentational advantages of LLMs over humans may not be enough to give LLMs a competitive edge against most of our expert debaters.

3.3. RQ3: Rater Stance Change

Finally, we evaluate how rater stance changes from engaging with the debate, and whether the magnitude of this change varies depending on debater identity (LLM or human). Specifically, we measure stance change as the difference between the rater's

Group	N Ratings	N Debaters	Median	Mean	SD	95% CI (Mean)
Human: Low	135	5	75.0	67.7	26.8	[63.9, 71.6]
Human: Medium	151	6	76.0	69.2	24.0	[66.2, 72.5]
Human: High	208	8	76.0	72.7	19.9	[69.8, 75.8]
LLM	520	1	78.5	75.2	17.1	[73.5, 77.1]

Contrast	Mean Diff	SE	t	p	95% CI
LLM vs Low	+7.56	2.50	3.02	0.003	[3.27, 11.63]
LLM vs Medium	+6.07	2.21	2.74	0.006	[2.29, 9.51]
LLM vs High	+2.52	1.69	1.49	0.136	[-1.01, 5.95]

Table 2: **Comparison between LLM and human debate performance, split by human expertise level. [top]**: descriptive statistics for overall performance rating (0-100 scale). **[bottom]**: pairwise contrasts (LLM vs. human groups) using rater-clustered robust SEs and 10,000-sample 95% bootstrap CIs. Significant contrasts at $p<0.05$ highlighted in **bold**. Robust SEs: HC2.

Quality Dimension	Mean (LLM)	Mean (Human)	Δ (LLM–Human)	t	p
Language Formality	75.19	70.08	**5.10**	5.76	**<0.001**
Stance Confidence	82.53	77.44	**5.09**	4.82	**<0.001**
Rebuttal Quality	71.66	66.68	**4.97**	3.80	**0.001**
Argument Clarity	79.90	75.35	**4.55**	4.06	**<0.001**
Issue Knowledge	76.60	73.11	**3.49**	3.15	**0.011**
Argument Logic	75.76	72.80	2.96	2.27	0.112
Argument Engagingness	71.31	68.50	2.81	2.29	0.112
Argument Convincingness	70.44	67.72	2.71	1.76	0.116
Use of Evidence	56.58	54.35	2.23	2.15	0.112
Argument Originality	62.56	60.45	2.11	1.90	0.116

Table 3: **Mean ratings across ten granular dimensions of argument quality for LLM vs. human debaters**. Reported p-values are for paired t-tests with Holm-Bonferroni correction across attributes. Significant differences at p<0.05 are highlighted in **bold**.

Variable	Coef.	SE	z	OR	p
Δ **Knowledge**	0.056	0.018	3.06	1.057	0.002
Δ **Convincing**	0.060	0.022	2.78	1.062	0.005
Δ **Rebuttal**	0.043	0.016	2.62	1.043	0.009
Δ **Engagingness**	0.049	0.022	2.21	1.050	0.027
Δ Evidence	0.020	0.011	1.79	1.020	0.074
Δ Logic	0.031	0.022	1.42	1.031	0.156
Δ Originality	0.020	0.018	1.15	1.020	0.251
Δ Formality	-0.015	0.015	-1.01	0.985	0.311
Δ Clarity	0.023	0.024	0.97	1.023	0.331
Δ Confidence	0.004	0.019	0.20	1.004	0.841

Table 4: **Logistic regression of debate winner choice**. Predictors are rater-level score differences (LLM − Human) on the ten granular attributes. We report coefficients, robust standard errors, z, odds ratios (OR), and p-values. Rows sorted by $|z|$. Model uses robust SEs (HC1), $n = 520$, Pseudo $R^2 = 0.668$.

self-reported stance on the motion from before they engaged and their post-debate stance, where positive values indicate a shift towards the Proposition position. We then fit two OLS regressions with heteroskedasticity-robust standard errors.

For **Model 1**, we regress stance change on an indicator variable for which side the rater chose as the winner (1 if the rater picked Proposition as winner, 0 if they picked Opposition). We find that stance change reliably tracks the side that raters judge as the winner (Table 5): When raters pick the Opposition as winner, their stance shifts an average of 9.39 points (0-100 scale) towards the Opposition side (p<0.001). Conversely, when raters pick the Proposition, their stance shifts an average of 5.90 points towards the Proposition side (p<0.001).

For **Model 2**, we add a debater identity indicator (1 if the Proposition side was argued by the AI, 0 if by a human). If, on average, the LLM was more persuasive than the human debaters in our study, we would expect to find a significant positive association. However, we find no such thing (Table 6): The coefficient for the debater identity indicator is not significant, and a nested model F-test (F(1,517)=0.02, p=0.888) further confirms that adding this indicator does not significantly improve model fit compared to Model 1. We note that, in future work, a larger sample may be able to identify small but significant effects of debater identity.

Overall, raters' stance therefore clearly tends to shift toward the side they judged as winner, whereas the identity of the winner (human or LLM) has no significant effect.

4. Discussion

RQ1 (Performance Comparison) Our results show **that a state-of-the-art LLM can compete effectively with human debaters in multi-turn**

Oxford-style debates. The LLM significantly outperforms less experienced debaters while performing on par with highly experienced debaters (§3.1). These findings extend previous single-turn [Durmus et al., 2024, Goldstein et al., 2024, Hackenburg et al., 2025c] and multi-turn studies of LLM persuasion and argumentation [Costello et al., 2024, Hackenburg et al., 2025b] by demonstrating sustained argumentative competence in a dynamic and highly competitive debate setting. The LLM maintains coherence across six turns and responds to opponent arguments in a way that is so convincing that raters often declare the LLM the debate winner. These are capabilities that go beyond generating persuasive stand-alone text. The LLM's relative strength in rebuttal quality also represents a notable advance over earlier AI debate systems like Project Debater [Slonim et al., 2021]. Drawing on the Elaboration Likelihood Model [Petty and Cacioppo, 1986], our study primarily captures the argument dimension of persuasion. Future work could explore how source factors interact with LLM argumentation: for instance, assigning the LLM a named persona or domain-specific background may influence perceived credibility and, in turn, persuasive impact. Similarly, recipient characteristics warrant further investigation — raters with formal debate experience may apply stricter evaluative criteria, particularly on substantive dimensions, which could widen or narrow the performance gap we observe.

RQ2 (Predictors of Winner Choice) At a more granular level, we found that **the LLM outperforms human debaters on specific dimensions of argument quality** (§3.1). While the LLM consistently outperforms humans on presentational dimensions (Clarity, Confidence, Formality), it does not outperform human debaters on most substantive dimensions (Convincingness, Evidence, Originality). These substantive dimensions, however, are most strongly associated with third-party winner choice (§3.2). This "formality paradox" suggests that, even when LLMs excel at rhetorical presentation, they would need to achieve comparable advantages in substantive argumentation to consistently place them above expert human debaters.

RQ3 (Rater Stance Change) Finally, our results show that **raters tend to shift their stance towards the debate side that they chose as winner**. Debater identity (human or LLM), on the other hand, did not significantly explain which side raters choose as winner (§3.3). This suggests that – in our setting, where raters do not know that one debater is an LLM – raters are not biased towards human- or LLM-written content per se, but rather shift their stance towards whoever they think produces the most convincing arguments.

Variable	Coef.	SE	t	p
Intercept	-9.39	1.37	-6.84	$<$0.001
Winner is Proposition	15.29	1.69	9.04	$<$0.001
$R^2 = 0.140$ $N = 520$				

Table 5: **OLS regression of stance change on winner choice** (Model 1). Stance change is measured as the difference in the rater's post-debate vs. pre-debate stance. Robust SEs: HC2.

Variable	Coef.	SE	t	p
Intercept	-9.59	2.07	-4.63	$<$0.001
Winner is Proposition	15.29	1.69	9.03	$<$0.001
Proposition is LLM	0.27	1.95	0.14	0.888
$R^2 = 0.140$ $N = 520$				

Table 6: **OLS regression of stance change on winner choice + debater identity** (Model 2). Stance change is measured as the difference in the rater's post-debate vs. pre-debate stance. Significant coefficients at p$<$0.05 in **bold**.

5. Related Work

5.1. Single-Turn Persuasion

Single-turn evaluations ask models to produce a standalone argument that humans judge for convincingness. Past natural language generation systems struggled to capture the flexible, context-sensitive reasoning needed for persuasion [Al Hashemi et al., 2015, Gatt and Krahmer, 2018]. LLMs raised the ceiling. GPT-3 enabled fluent, on-topic arguments [Brown et al., 2020], and across one-shot studies LLM outputs are often judged to be as persuasive as human writing [Gilardi et al., 2023, Carrasco-Farre, 2024, Goldstein et al., 2024, Bai et al., 2025, Bozdag et al., 2025, Hackenburg et al., 2025a]. However, single-turn settings may overstate argumentative competence: without an adversary, reasoning gaps and unsupported claims go unchallenged [Lisker et al., 2025].

5.2. Multi-Turn Persuasion

A smaller body of work studies LLM argumentative competence in multi-turn, dialogic settings, the aspect most directly relevant to our study. Costello et al. [2024] find that extended GPT-4 dialogues can durably reduce conspiracy beliefs, and Salvi et al. [2025] show that GPT-4 is broadly persuasive in open-ended conversation. Flamino et al. [2025] examine LLMs in debate-like exchanges against humans, but rely on automated evaluation rather than blinded human judges, leaving it unclear how well automated scores capture true argu-

mentative quality. More broadly, dialogue research shows that persuasive success depends on anticipating objections and delivering timely, targeted replies, not just text quality [Tan et al., 2016, Niculae and Danescu-Niculescu-Mizil, 2016, Durmus and Cardie, 2019]. These findings motivate structured, adversarial evaluation of LLM argumentation with human oversight [Scheurer et al., 2024, Jones and Bergen, 2026, Williams et al., 2024]. Our study contributes to this setting by providing the first blinded, head-to-head assessment of LLM argumentative competence in a fully adversarial, multi-turn debate against expert humans.

5.3. Formal Debate and Measurement

Formal debate, with fixed turns and word budgets, sharpens evaluation of sustained reasoning under pressure [Irving et al., 2018]. The most prominent prior system is IBM's Project Debater [Slonim et al., 2021], an autonomous debating system that competes against human debaters in structured, multi-turn exchanges; expert judges, however, still preferred the human on persuasiveness and style. More recent evaluations of LLMs in debate settings rely on automated scoring: "GPT-as-a-judge" metrics correlate with human verdicts but exhibit systematic biases [Jones and Bergen, 2026, Liu et al., 2024], underscoring the need for blinded human raters. To our knowledge, no prior work has run a double-blind, head-to-head evaluation of a state-of-the-art LLM against expert human debaters with independent, blinded third-party judges; our study fills this gap.

On outcomes, many NLP studies equate persuasion with attitude change [Tan et al., 2016], echoing social-psychological theories of central processing [Petty and Cacioppo, 1986]. Because stance shift can conflate rational persuasion with manipulation [Jones and Bergen, 2026], we treat blinded win/loss as the *primary* metric and report stance change as a secondary outcome.

6. Conclusion

State-of-the-art LLMs can produce highly persuasive texts, but their capacity for sustained argumentative competence in competitive multi-turn settings has been left unexplored. In this study, we therefore benchmarked an open-weight LLM in multi-turn Oxford-style debates against expert human debaters. Based on blinded rater judgments, the LLM performed competitively, winning 51.15% of debates. Compared to human debaters, raters found the relative strengths of the LLM to be presentational and structural, while rating it on par with humans on substantive criteria. Debate outcomes were best explained by differences in substantive argument quality. Relative advantages in being judged Convincing, Knowledgeable and Engaging predicted third-party winner choice, whereas advantages on presentation alone did not. Rater stance change from engaging with the debates tracked the chosen winner, but not debater identity.

Overall, our results suggest that state-of-the-art LLMs can sustain adversarial debate even in multi-turn debates, at a level that is competitive with human experts. While our study is limited in size and scope, our methodology provides a structured framework for assessing sustained argumentative competence that addresses the limitations of single-turn evaluations. We hope that future work can expand our approach to larger participant pools, multiple models, and other debate modalities, to substantiate how competitive debate performance generalises and inform the development of more robust AI evaluation protocols.

Limitations

Scope and Sample Size The most significant limitations of our study are created by budget constraints. The power of our analyses is limited by the size of our debater and rater pools. Rater disagreement on debate winners as well as argument quality scores introduces additional noise. Expert debaters were recruited only at the University of Oxford. Raters had limited debate experience as well as skewed demographics that may have shaped their ratings and thus overall results, especially given the rater disagreement we observed. Our study also benchmarks just a single model, decoding profile, and prompting strategy. We hope that future work can build on our evaluation protocol, recruiting larger participant pools, comparing additional models and ablating over prompts and parameters to produce more robust evidence.

Debate Format Competitive Oxford-style debate is typically spoken rather than written, and winners for each debate are judged by a large debate audience. Future work could expand the modality of our work to audio, and – budget allowing – substantially increase the size of the rater pool to match this format. The 150-word maximum turn length we chose to limit human data collection cost could also be increased, to allow for more expressive and in-depth argumentation from both LLMs and humans.[4] Lastly, topic coverage was narrow (ten debate motions), and we cannot rule out topical overlap with LLM training data. Future work could

[4] Please refer to the full debate transcripts in our data release to assess the quality and argumentative depth achievable within this format.

deliberately construct novel (e.g. highly current) motions to address this concern.

Measuring Persuasion While we do find significant stance change in raters when comparing pre- and post-debate stance, we cannot make strong causal claims due to the absence of a randomised control. We also do not have baselines (e.g. human-human debates) that we could compare the potential persuasive effects from engaging with human-LLM debates to. We hope that these limitations can be addressed in future work more directly focused on multi-turn persuasion rather than argumentative competence and debate performance. Relatedly, power was limited for debater identity effects and persuasion was measured only as immediate stance change. Stance change durability was not tested. Future work should increase sample size, include longitudinal follow-ups, and preregister multiplicity control for dimensional comparisons.

Ethics Statement

This study was approved by the ethics review board of the Oxford Internet Institute, University of Oxford. All participants (debaters and raters) provided informed consent. Debates were collected via a custom web interface. Transcripts shown to raters were anonymised ("Debater A/B"), with self-references removed. We applied data minimisation and stored only pseudonymised identifiers for debaters and raters. Debaters were compensated with a £20 gift card for completing five debates. Raters were compensated at approximately £10/hour. When collecting ratings, we followed best practices in protecting rater welfare [Vidgen et al., 2019], although we note that we found no offensive or otherwise clearly harmful content in any of the debate transcripts.

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Appendix

A. Debate format: protocol and judging principles

Roles and turn order. Two sides, *Proposition* (for the motion) and *Opposition* (against), engage in a six-turn, text-only exchange: Opening (Prop), Opening (Opp), Rebuttal (Prop), Rebuttal (Opp), Closing (Prop), Closing (Opp). This adversarial, two-sided structure mirrors Oxford/British Parliamentary practice [Eckstein and Llano, 2017, p. 1].

Word budget and pacing. Each turn is constrained to **100–150 words**. Open-ended prep or external research were disallowed in our platform implementation to preserve symmetry and focus on in-the-moment argumentation (no links or citations required).

Admissible argument types. Speakers may advance *principled* (normative/value-based) and/or *practical* (consequence-based) claims. Consistent with Oxford/WUDC doctrine, the persuasive burden is to offer a coherent, reasoned case accessible to the "ordinary intelligent voter," rather than to overwhelm with evidence [WUDC, 2020, p. 15, p. 40].

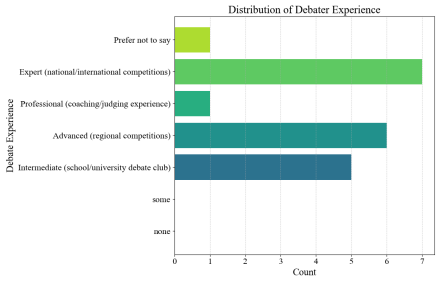
Evidence and examples. Evidence and examples are welcome but *secondary*: they should illustrate and support the core reasoning rather than replace it. An argument with a clear logical chain is preferred to one that merely cites an example without coherence [WUDC, 2020, p. 35].

Value weighing and clash. Debaters are expected to weigh competing values explicitly (e.g., autonomy vs. welfare) and to engage the opponent's *key* claims with focused rebuttal. Judgment in this tradition prioritizes principled reasoning and logical consistency over raw evidence counts [WUDC, 2020, p. 20].

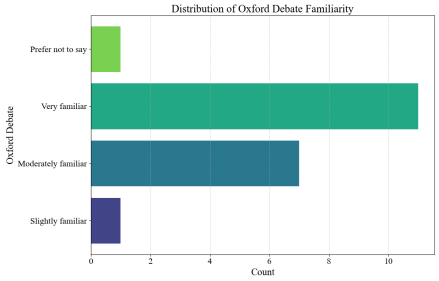
Anonymity and blinding (implementation detail). Transcripts presented to raters were relabeled as "Debater A/B," with self-references scrubbed; raters were not told that one side could be an LLM.

Ballot. Raters selected a single winner per debate (no ties). This winner choice served as the primary outcome; separate 0–100 sliders captured perceived *Knowledge, Confidence, Clarity, Logic, Formality, Evidence, Engaging, Originality, Rebuttal, Convincingness*, and overall *Performance* (see Appendix D).

B. Additional demographics



(a) Distribution of self-reported debate experience levels.



(b) Distribution of self-reported familiarity with the debate format.

Figure 3: Debater Experience and Format Familiarity (Phase 1, $N = 20$).

C. LLM Prompt Templates

This appendix details the prompt templates used to generate the LLM's responses. A system prompt was prepended to every API call, followed by a turn-specific user prompt.

C.1. System Prompt

The following description outlines the function of the immutable system instruction prepended to every API call. The `[side]` and `[motion]` variables were dynamically inserted based on the debate setup. `[side]` was replaced with either `PROPOSITION` or `OPPOSITION`.

C.2. Opening Turn Template

This template was used to generate the opening argument and was passed as the "user" prompt. The `[motion]` and `[side]` variables were replaced with the full title of the debate topic and the assigned stance, respectively.

> Write your opening statement for the motion: "`[motion]`"
>
> As the `[side]` side, you must:

Demographic	Category	Count (N=61)	Proportion (%)
Age	18–29 years	15	24.59
	30–39 years	12	19.67
	40–49 years	5	8.20
	50+ years	29	47.54
Gender	Female	22	36.07
	Male	39	63.93
Education	High school or equivalent	3	4.92
	A-levels or equivalent	7	11.48
	Undergraduate degree	23	37.70
	Post-graduate degree (Master's)	13	21.31
	Doctorate (PhD)	12	19.67
	Other / Vocational	3	4.92
English proficiency	Native speaker	55	90.16
	Non-native (fluent)	6	9.84
Debate experience	None	29	47.54
	Some	22	36.07
	Moderate	9	14.75
	Extensive	1	1.64
Oxford debate familiarity	Not familiar	21	34.43
	Somewhat familiar	3	4.92
	Very familiar	37	60.66
Political ideology	Very Left-Wing	1	1.64
	Moderately Left-Wing	2	3.28
	Centrist	12	19.67
	Moderately Right-Wing	19	31.15
	Very Right-Wing	24	39.34
	Prefer not to say	3	4.92

Table 7: Summary of rater demographics (Phase 2, $N = 61$).

- Clearly state your stance.
- Present your strongest arguments clearly and persuasively. These may be principled (moral/philosophical), practical (real-world consequences), or a combination, depending on what best supports your side.
- Use clear structure and sign-posting ("First,... Second,...") to guide the reader.
- End with a compelling summary that frames the debate in your favor.

Keep your statement between **100–150 words**. Do not mention that you are an AI.

C.3. Rebuttal Turn Template

This template was used for the rebuttal turn. It included the opponent's arguments and instructed the model to refute them. The `[Previous arguments in this debate]` section was dynamically populated with all preceding turns.

> Write your **rebuttal statement** in response to your opponent's opening statement in the debate.
>
> As the `[side]` side, you should:
>
> - Identify the **key claims** made by your opponent.
> - Refute their logic or values with clear counter-reasoning.
> - Defend your original arguments or restate them more forcefully.
> - **Compare the competing values**, show why your side's priorities matter more.
> - Use both principled and practical responses if applicable.
> - Use clear sign-posting to structure your argument.

Keep your response between 100–150 words.

Previous arguments in this debate:

`[SIDE] [TURN_TYPE]: [Argument content]`

`[SIDE] [TURN_TYPE]: [Argument content]`

...

Your rebuttal must be between 100–150 words. Do not mention that you are an AI.

C.4. Closing Turn Template

This template was used for the closing statement. The `[All previous arguments]` section was populated with the full, chronologically ordered transcript.

Write your **closing statement** for the debate: "`[motion]`"

As the `[side]` side, you should:

- Recap your most persuasive principled and practical arguments.
- Address the major points of contention raised in the debate.
- **Respond to your opponent's most recent arguments**, showing why they are weaker or flawed.
- Weigh the competing values explicitly, make the case for why your values should guide the outcome.
- Finish with a clear, persuasive summary of why the audience should support your position.

Keep your closing statement between **100–150 words**.

All previous arguments in this debate (chronological order):

`[SIDE] [TURN_TYPE] ([PARTICIPANT]): [Argument]`

`[SIDE] [TURN_TYPE] ([PARTICIPANT]): [Argument]`

...

Your closing must be between 100–150 words. Do not mention that you are an AI.

D. Rater Instructions and Evaluation Rubric

This appendix provides the complete materials presented to Phase 2 raters, including the consent form, attention check, and the evaluation rubric used for scoring the debates.

D.1. Rater Onboarding and Instructions

Informed Consent Form

The following text was presented to all raters recruited via Prolific before they could begin the study.

> You are invited to take part in a survey where you evaluate transcripts from one-on-one debates about a range of political issues. We expect this survey to take around 30 minutes. Before deciding whether to participate, please read this information carefully.
>
> **Data Collection and Use:** In this survey, we will collect (i) your ratings of 10 anonymised debate transcripts (300–400 words each), based on clarity, logical coherence, use of evidence, rhetorical appeal, and overall performance; (ii) your choice of which side performed better in each debate; and (iii) your Prolific ID, which will be converted to a study-specific anonymous ID. Your responses will be stored securely on University servers for up to five years. Aggregated results may appear in academic publications or presentations. Individual participants will not be identifiable.

Anonymity and Confidentiality. All data will be stored securely. Published results will contain no personally identifying information. Anonymised participant-level data will be made publicly available, but your Prolific ID will never be shared.

Voluntary Participation. Participation is entirely voluntary. You may withdraw at any time before submitting your final questionnaire. After submission, data cannot be withdrawn as it is immediately anonymised and aggregated.

Compensation. You will be paid £5.50 via Prolific for approximately 40 minutes of work (£8.25 per hour).

Ethical Approval. This study has been approved by the Oxford Internet Institute Departmental Research Ethics Committee under CUREC guidelines.

Attention Check

After the consent form, raters were presented with a "Warm-Up Question" as an attention check.

Instructions: "This is an attention check to make sure that you are reading all questions carefully. Please ignore the question about convincing writing below and simply move the slider somewhere between 30 and 40. Thank you."

Question: "How convincing do you generally find emotional appeals in writing?" (slider 0–100).

D.2. Evaluation Interface and Rubric

Evaluation Interface

The evaluation interface presented the debate transcript on the left side of the screen and the rating sliders on the right. The motion was displayed at the top. Raters evaluated 10 debates in total, rating each side on 11 dimensions and then choosing an overall winner.

Rating Dimensions

Raters used a slider from 0 ("Not at all") to 100 ("Extremely") for each of the following dimensions:

Knowledge: How much does this debater know about the issue referenced in the motion?

Confidence: How confident is the debater in their stance on the motion?

Clarity: How clear were this debater's arguments?

Logic: How logical were this debater's arguments?

Formality: How formal is the language used by this debater?

Evidence: How much did this debater rely on evidence to make their point?

Engaging: How engaging did you find the arguments used by this debater?

Originality: How original did you find the arguments used by this debater?

Rebuttal: How well did this debater address and rebut their opponent's key points?

Convincing: How convincing did you personally find this debater's arguments?

Performance: How would you rate the overall performance of this debater?

E. Supplementary Statistical Results

E.1. Model specifications for main-text analyses

Linear mixed-effects model for Performance. To test whether the LLM–human gap varies with human expertise, we fit a mixed model with rater random intercepts:

$$\begin{aligned}\mathrm{Perf}_{ij} = (\beta_0 + u_{0j}) + \beta_1\,\mathrm{is\_human}_i + \beta_2\,\mathrm{expertise}_i \\ + \beta_3\,(\mathrm{is\_human}_i \times \mathrm{expertise}_i) + \varepsilon_{ij}.\end{aligned} \tag{1}$$

Here, $\mathrm{Perf}_{ij} \in [0, 100]$ is rater j's score for debater i; $\mathrm{is\_human}_i \in \{0, 1\}$; $\mathrm{expertise}_i$ is an ordinal self-report; $u_{0j} \sim \mathcal{N}(0, \sigma_u^2)$ is a rater random intercept; and $\varepsilon_{ij} \sim \mathcal{N}(0, \sigma^2)$. Estimates are in Appendix E.7; pseudo-R^2 in Appendix F.3.

E.2. Model specification for winner choice (RQ2)

Logistic model using score differences. Winner choice was modeled with a logistic regression using *differences* between the two debaters' ratings on the ten granular dimensions (Debater A minus Debater B):

$$\begin{aligned}\mathrm{logit}[P(\mathrm{win}_A)] = \beta_0 + \beta_1\Delta\mathrm{Clarity} + \beta_2\Delta\mathrm{Confidence} \\ + \beta_3\Delta\mathrm{Convincing} + \beta_4\Delta\mathrm{Engaging} \\ + \beta_5\Delta\mathrm{Evidence} + \beta_6\Delta\mathrm{Formality} \\ + \beta_7\Delta\mathrm{Knowledge} + \beta_8\Delta\mathrm{Logic} \\ + \beta_9\Delta\mathrm{Originality} + \beta_{10}\Delta\mathrm{Rebuttal}.\end{aligned}$$

Estimates are in Table 4 (main text); full output in Appendix E.7.

Interpreting effects. Odds ratios are $\exp(\beta_k)$; for `convincing_diff`, OR $\approx \exp(0.061)$.

E.3. Model specifications for stance change (RQ3)

Outcome. $\Delta\mathrm{stance}_i = \mathrm{post\_stance}_i - \mathrm{pre\_stance}_i$ on the 0–100 scale. Positive values indicate movement toward Proposition.

Model 1: winner choice only. $\Delta\mathrm{stance}_i = \alpha_0 + \alpha_1\,\mathbb{I}\{\text{winner is Prop.}\}_i + \varepsilon_i$.

Model 2: winner choice + debater identity. $\Delta\mathrm{stance}_i = \gamma_0 + \gamma_1\,\mathbb{I}\{\text{winner is Prop.}\}_i + \gamma_2\,\mathbb{I}\{\text{Prop. is AI}\}_i + \varepsilon_i$.

Estimation and inference. Both models use OLS with HC2 robust SEs. Full outputs in Appendix E.7; diagnostics in Appendix F.3.

E.4. Full Correlation Matrices

Table 8: LLM Debaters: Pearson's r Values

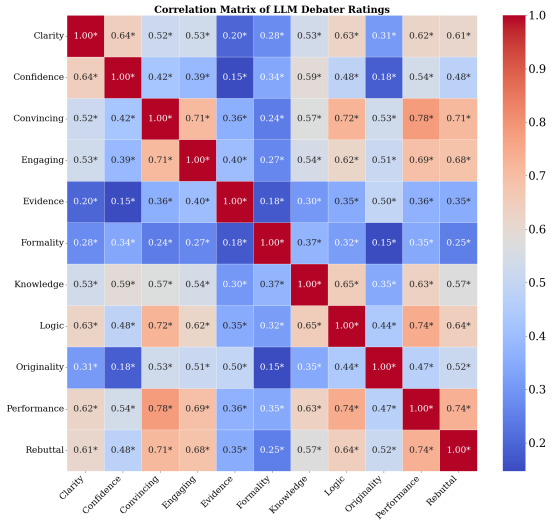
	Knwl	Conf	Clar	Logic	Form	Evid	Engag	Orig	Rebut	Conv	Perf
Knowledge	1.00	0.587	0.534	0.649	0.374	0.302	0.544	0.346	0.574	0.570	0.633
Confidence	0.587	1.00	0.644	0.482	0.339	0.147	0.388	0.181	0.477	0.424	0.539
Clarity	0.534	0.644	1.00	0.626	0.275	0.197	0.531	0.307	0.610	0.520	0.621
Logic	0.649	0.482	0.626	1.00	0.315	0.348	0.620	0.441	0.645	0.724	0.744
Formality	0.374	0.339	0.275	0.315	1.00	0.177	0.265	0.148	0.248	0.243	0.346
Evidence	0.302	0.147	0.197	0.348	0.177	1.00	0.398	0.497	0.351	0.362	0.365
Engaging	0.544	0.388	0.531	0.620	0.265	0.398	1.00	0.511	0.684	0.709	0.690
Originality	0.346	0.181	0.307	0.441	0.148	0.497	0.511	1.00	0.517	0.531	0.470
Rebuttal	0.574	0.477	0.610	0.645	0.248	0.351	0.684	0.517	1.00	0.713	0.735
Convincing	0.570	0.424	0.520	0.724	0.243	0.362	0.709	0.531	0.713	1.00	0.783
Performance	0.633	0.539	0.621	0.744	0.346	0.365	0.690	0.470	0.735	0.783	1.00

Table 9: Human Debaters: Pearson's r Values

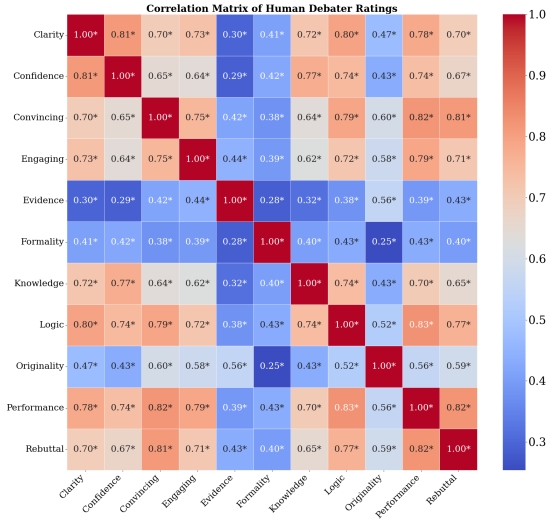
	Knwl	Conf	Clar	Logic	Form	Evid	Engag	Orig	Rebut	Conv	Perf
Knowledge	1.0	0.774	0.717	0.742	0.404	0.316	0.624	0.433	0.652	0.637	0.701
Confidence	0.774	1.0	0.811	0.744	0.421	0.286	0.641	0.434	0.670	0.650	0.737
Clarity	0.717	0.811	1.0	0.796	0.406	0.297	0.726	0.472	0.696	0.698	0.784
Logic	0.742	0.744	0.796	1.0	0.431	0.380	0.716	0.522	0.767	0.793	0.827
Formality	0.404	0.421	0.406	0.431	1.0	0.285	0.393	0.254	0.397	0.381	0.432
Evidence	0.316	0.286	0.297	0.380	0.285	1.0	0.445	0.559	0.434	0.415	0.388
Engaging	0.624	0.641	0.726	0.716	0.393	0.445	1.0	0.580	0.712	0.754	0.788
Originality	0.433	0.434	0.472	0.522	0.254	0.559	0.580	1.0	0.591	0.600	0.562
Rebuttal	0.652	0.670	0.696	0.767	0.397	0.434	0.712	0.591	1.0	0.811	0.823
Convincing	0.637	0.650	0.698	0.793	0.381	0.415	0.754	0.600	0.811	1.0	0.819
Performance	0.701	0.737	0.784	0.827	0.432	0.388	0.788	0.562	0.823	0.819	1.0

E.5. Correlation Heatmaps

See Figure 4.



(a) LLM Debater Ratings



(b) Human Debater Ratings

Figure 4: Pearson correlation matrices for the 11 performance rating dimensions, shown separately for (a) the LLM and (b) human debaters. Significant correlations ($p < 0.05$) are noted in the figures.

E.6. Rating distributions (KDE)

The kernel density plots in Figures 5 and 6 complement Table 3 in the main text, visualizing rater scores (0–100) for the LLM and human debaters across all eleven dimensions.

E.7. Full Regression Model Outputs

Linear Mixed-Effects Model

```
  Mixed Linear Model Regression Results
=====================================================
Model: MixedLM       Dep.Var.: performance
N.Obs.: 1040         Method: REML
N.Groups: 61         Scale: 351.1010
Min.grp: 2           Log-Lik.: -4558.4147
Max.grp: 20          Converged: Yes
Mean.grp: 17.0
-----------------------------------------------------
                Coef.    SE      z      P>|z|
-----------------------------------------------------
Intercept       76.837   2.750  27.937  0.000
is_human       -16.656   3.571  -4.664  0.000
expertise       -0.547   0.826  -0.663  0.508
is_human:exp.    3.962   1.146   3.456  0.001
Group Var       58.049   0.809
=====================================================
```

Logistic Regression: Predicting Debate Winner

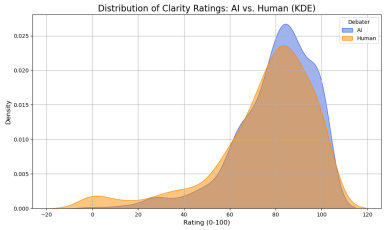
```
Dep.Var.: ai_won     N.Obs.: 520
Model: Logit         Pseudo R2: 0.6677
Method: MLE          Log-Lik.: -119.71
Converged: True      LL-Null: -360.25
Cov.: nonrobust      LLR p: 4.883e-97
-----------------------------------------------------
                  coef    SE      z      P>|z|
-----------------------------------------------------
const           -0.1095  0.171  -0.642  0.521
knowledge_diff   0.0555  0.017   3.186  0.001
confidence_diff  0.0038  0.019   0.204  0.839
clarity_diff     0.0232  0.019   1.248  0.212
logic_diff       0.0307  0.018   1.662  0.097
formality_diff  -0.0152  0.013  -1.135  0.257
evidence_diff    0.0201  0.012   1.668  0.095
engaging_diff    0.0487  0.020   2.484  0.013
originality_diff 0.0201  0.017   1.199  0.231
rebuttal_diff    0.0426  0.016   2.684  0.007
convincing_diff  0.0605  0.016   3.873  0.000
-----------------------------------------------------
Note: 0.18 fraction perfectly predicted.
```

OLS: Stance Change on Winner Choice (Model 1)

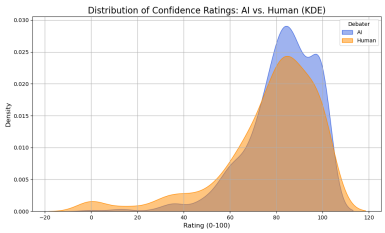
```
Formula: stance_change ~ winner_is_Proposition
Robust SEs: HC2   N=520   R2=0.1400
-------------------------------------------------
                        coef    SE     P>|z|
-------------------------------------------------
Intercept             -9.3934  1.373  0.000
winner_is_Prop.       15.2884  1.692  0.000
-------------------------------------------------
```

OLS: Stance Change with Debater Identity (Model 2)

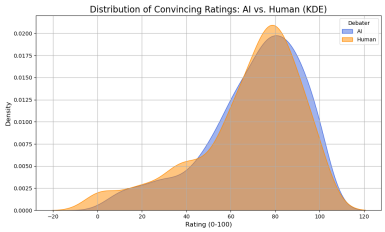
```
Formula: stance_change ~
  winner_is_Proposition + Proposition_is_AI
Robust SEs: HC2   N=520   R2=0.1400
-------------------------------------------------
                        coef    SE     P>|z|
-------------------------------------------------
Intercept             -9.5890  2.069  0.000
winner_is_Prop.       15.2882  1.693  0.000
Proposition_is_AI      0.2743  1.946  0.888
-------------------------------------------------
```



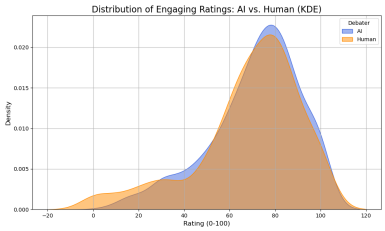
(a) Clarity



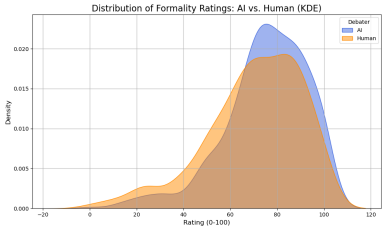
(b) Confidence



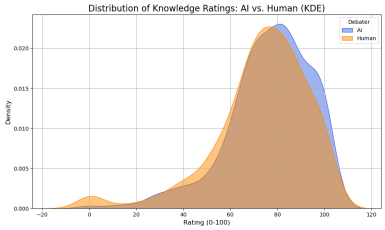
(c) Convincing



(d) Engaging

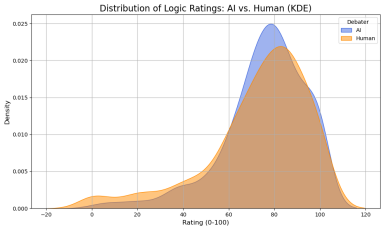


(e) Formality

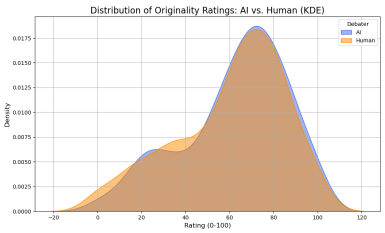


(f) Knowledge

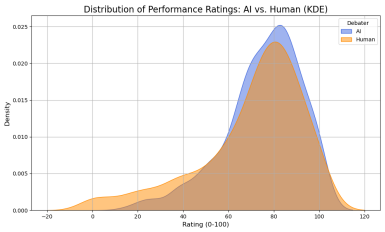
Figure 5: KDE plots of rater scores for the LLM (blue) and human debaters (orange) across eleven quality dimensions (a)–(f).



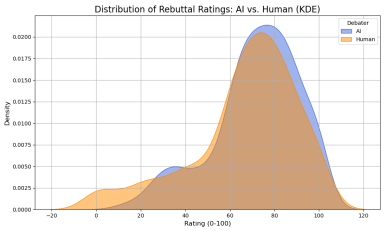
(a) Logic



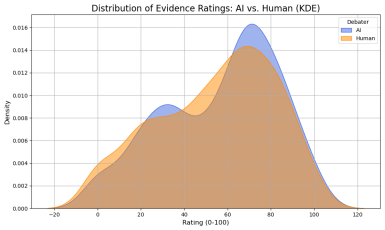
(b) Originality



(c) Performance



(d) Rebuttal



(e) Evidence

Figure 6: KDE plots of rater scores for the LLM (blue) and human debaters (orange) across eleven quality dimensions, continued from Figure 5.

F. Robustness Checks

F.1. Inter-Rater Agreement

Krippendorff's α for categorical winner choice was 0.078. While only slight, this positive value confirms that rater decisions were not random, supporting the validity of the aggregate win rate as a meaningful effect.

F.2. Reliability and Consistency Checks

Internal consistency (Cronbach's α). AI ratings: $\alpha = 0.900$; Human ratings: $\alpha = 0.937$. Both exceed the conventional threshold of 0.9, indicating that the 11 dimensions coherently measure overall perceived quality.

Inter-rater reliability (ICC$_{2,k}$). ICC values for AI ratings: Knowledge 0.005, Confidence 0.013, Clarity 0.049, Logic 0.030, Formality 0.000, Evidence 0.005, Engaging 0.006, Originality 0.000, Rebuttal 0.065, Convincing 0.036, Performance 0.092.

ICC values for Human ratings: Knowledge 0.225, Confidence 0.251, Clarity 0.221, Logic 0.175, Formality 0.025, Evidence 0.006, Engaging 0.130, Originality 0.102, Rebuttal 0.153, Convincing 0.158, Performance 0.168.

ICC values are generally low, particularly for AI debaters, indicating considerable between-rater variability. While individual ratings are noisy, aggregation provides a more stable measure.

F.3. Model-Specific Robustness Checks

F.3.1. Linear Mixed-Effects Model

Goodness of fit (Pseudo R^2). Marginal $R^2 = 0.029$ (fixed effects only); Conditional $R^2 = 0.167$ (fixed + random effects).

Homoscedasticity. Figure 7 shows the residuals vs. fitted plot. Variance is not constant (wider on the left, narrower on the right), indicating heteroscedasticity; the interaction effect may be slightly over- or under-estimated.

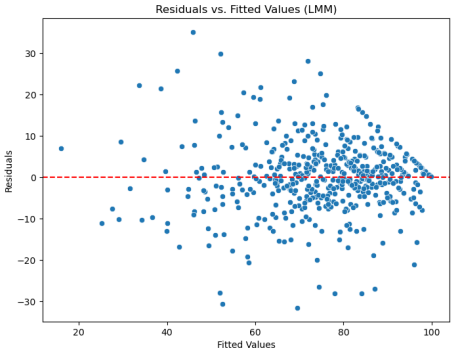


Figure 7: LMM residuals vs. Fitted plot.

Normality of residuals. Figure 8 shows the Q-Q plot; residuals are approximately normal in the middle of the distribution.

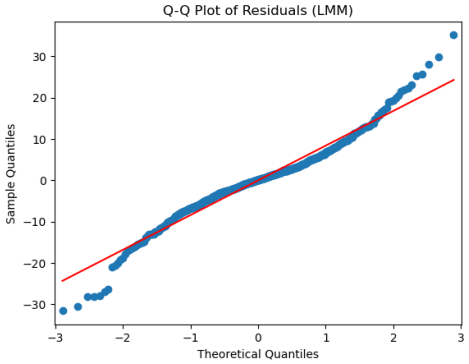


Figure 8: LMM Q-Q plot of Residuals.

F.3.2. Logistic Regression: Multicollinearity

feature	VIF
const	1.099829
knowledge_diff	3.327595
confidence_diff	3.583808
clarity_diff	3.992397
logic_diff	5.160943
formality_diff	1.261982
evidence_diff	1.803123
engaging_diff	4.342569
originality_diff	2.434143
rebuttal_diff	3.888235
convincing_diff	5.204545

All VIF values are below 10. `logic_diff` and `convincing_diff` are above 5, indicating moderate multicollinearity, though not at a problematic level.

F.3.3. Beta Regression

Dispersion. Pearson Chi^2/Df$_{\text{resid}} = 0.253$, suggesting underdispersion. This may yield optimistically small SEs and p-values.

GLMM robustness check. To verify that clustering within raters does not invalidate the independence assumption, we re-ran the model as a GLMM with a random intercept for `prolific_id`:

```
  Mixed Linear Model Regression Results
=====================================================
Model: MixedLM  Dep.Var.: post_stance_scaled
N.Obs.: 520     Method: REML
N.Groups: 61    Scale: 0.0386
Min.grp: 1      Log-Lik.: 94.6192
Max.grp: 10     Converged: Yes
Mean.grp: 8.5
-----------------------------------------------------
                   Coef.   SE      z      P>|z|
-----------------------------------------------------
Intercept          0.071  0.019   3.732  0.000
C(ai_side)[T.B]    0.005  0.019   0.265  0.791
pre_stance_scaled  0.855  0.027  31.299  0.000
Group Var          0.001  0.005
=====================================================
```

The GLMM results are substantively identical to the original Beta Regression: `pre_stance_scaled` remains large and highly significant; `C(ai_side)[T.B]` remains small and non-significant. The rater-level variance (Group Var) does not meaningfully change the conclusions.