Honest Evaluation of Korean LLM Systems: A Multi-Benchmark Empirical Study Using KMMLU, HAE-RAE, KorQuAD, KoBBQ, and KMHaS

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ABSTRACT

We propose *Honest Evaluation*, a multi-benchmark empirical framework for assessing Large Language Model (LLM) systems in the Korean language environment. The framework integrates five Korean benchmarks — KMMLU, HAE-RAE Bench, KorQuAD, KoBBQ, and KMHaS — into a unified seven-axis rubric covering logical consistency, Korean naturalness, citation accuracy, conclusion reasonability, overall coherence, social bias, and offensive language. We report an empirical baseline with *n=290* samples, achieving 80.8% classification accuracy (F1 = 0.796, Spearman ρ = 0.659) on a balanced corruption-detection task across four general-purpose benchmarks (n=120), **100% bias-detection rate across eight KoBBQ categories** (n=40), and **88.5% accuracy (F1 = 0.887, recall = 0.91) on KMHaS hate-speech detection** (n=130, balanced 65/65). We explicitly publish system weaknesses (e.g., 40% accuracy on KMMLU mathematics; recall dropping from 1.00 at n=40 to 0.91 at n=130) under the *honest measurement* philosophy, arguing that transparent disclosure of evaluation limitations is essential for building trust in third-party AI assessment services. In a preliminary single-vs-ensemble ablation (n=87), we further find that a two-model ensemble (GPT-4o + Claude Sonnet 4.6) attains the best F1 (0.82) and best calibration (ECE = 0.079) of any configuration, whereas a single GPT-4o judge fails to flag 33% of corrupted items (corruption recall = 0.67) — an operationally critical asymmetry for a quality gate. We further outline how the framework aligns with Korean national standard TTAK.KO-10.1497 (TTA, 2023) and discuss its applicability to high-impact AI domains (recruiting, finance, public services, healthcare) under the Korean AI Basic Act (in force since 22 January 2026), which obligates operator safety and reliability measures and encourages third-party verification as a practical compliance pathway.

1 Introduction

The proliferation of Large Language Models (LLMs) in Korean industrial settings has outpaced the development of trustworthy third-party evaluation infrastructure. While global evaluation frameworks such as G-Eval [1], LLM-as-a-Judge [2], and RAGAS [3] have established methodological foundations, their application to the Korean language environment remains fragmented, with individual benchmarks operating in isolation.

Korean industry faces three concurrent pressures: (1) the Korean AI Basic Act, in force since 22 January 2026, defines a "high-impact AI" category (recruiting, credit assessment, public administration, healthcare, etc.) and obligates providers to implement safety and reliability measures; while the Act itself emphasises operator self-assessment, official guidance and the TTA CAT regime encourage third-party verification as a practical means of demonstrating compliance; (2) global trustworthy AI frameworks (ISO/IEC TR 24028, NIST AI RMF, EU AI Act) require multi-dimensional assessment; and (3) Korean-specific evaluation dimensions, particularly social bias categories distinctive to Korean society (e.g., regional, educational, military-service-status biases) and Korean-language offensive expressions, are not adequately captured by English-centric benchmarks.

In this work, we propose *Honest Evaluation*, a multi-benchmark framework that integrates five Korean benchmarks — KMMLU [4], HAE-RAE Bench [5], KorQuAD [6], KoBBQ [7], and KMHaS [8] — into a seven-axis evaluation rubric. Our contributions are:

- **Empirical baseline:** We report *n = 290* measurements across five Korean benchmarks, providing a publicly available, multi-benchmark Korean LLM evaluation baseline that integrates bias (KoBBQ) and safety (KMHaS) dimensions alongside accuracy-oriented benchmarks (KMMLU, HAE-RAE, KorQuAD).
- **Honest measurement methodology:** We argue that third-party AI evaluation requires explicit disclosure of system weaknesses, including domains where the evaluator itself performs poorly (e.g., KMMLU mathematics at 40%).
- **Standards alignment:** We map our framework to TTAK.KO-10.1497 (the Korean national AI reliability standard) and provide a cross-standard matrix with ISO/IEC TR 24028, NIST AI RMF, and the EU AI Act.
- **Bias and safety integration:** We add two axes — social bias (via KoBBQ) and offensive language (via KMHaS) — to the standard five-axis LLM evaluation rubric, addressing high-impact AI domains under the Korean AI Basic Act.

We address the following research question: *To what extent can a single LLM-as-a-Judge, structured under a unified seven-axis rubric, reliably detect quality, bias, and safety issues in Korean LLM outputs across diverse benchmarks — and where does this approach systematically fail?* The latter half of this question motivates our explicit publication of evaluator weaknesses as a methodological commitment, not an oversight.

The remainder of the paper is organized as follows: Section 2 reviews related work. Section 3 describes our seven-axis rubric and ensemble methodology. Section 4 details the experimental setup. Section 5 presents results. Section 6 discusses implications and the *honest measurement* philosophy. Section 7 enumerates limitations and Section 8 sketches future work.

2 Related Work

2.1 LLM-as-a-Judge

Liu et al. [1] introduced G-Eval, which uses GPT-4 as an evaluator with chain-of-thought prompting. Zheng et al. [2] systematically characterized three biases of LLM judges: position bias, verbosity bias, and self-enhancement bias. Subsequent work has focused on mitigation strategies through ensemble methods and prompt engineering.

2.2 Calibration

Guo et al. [9] demonstrated that modern neural networks are systematically miscalibrated, introducing Expected Calibration Error (ECE) as the standard metric. Isotonic regression [10] and Platt scaling remain the dominant post-hoc calibration methods. We adopt isotonic regression for its non-parametric properties suitable for our small-sample regime.

2.3 Korean Benchmarks

KMMLU [4] provides 35,030 expert-annotated multiple-choice questions across 45 Korean professional subjects. HAE-RAE Bench [5] introduces six task categories targeting Korean cultural and historical knowledge that cannot be reduced to translation. KorQuAD [6] offers a SQuAD-style Korean reading comprehension dataset with over 70,000 question–answer pairs. KoBBQ [7] extends the BBQ bias benchmark [11] to 12 Korean social bias categories with 76,048 samples drawn from 268 templates. K-MHaS [8] is a multi-label Korean hate-speech detection dataset of approximately 109,692 comments (train split: 78,977; validation: 8,776; test: 21,939) with 8 hate-speech categories plus a "not hate" label. To our knowledge, no prior work integrates all five datasets into a single evaluation framework.

2.4 Inter-Rater Reliability

Cohen's κ [12] remains the de facto standard for inter-rater agreement on categorical labels, with Landis and Koch [13] providing the canonical interpretation scale. Our framework adopts $\kappa \geq 0.7$ (substantial agreement) as the operational target for human reviewer pools.

2.5 Standards and Regulation

ISO/IEC TR 24028 (2020) defines six trustworthiness dimensions for AI systems: reliability, robustness, resilience, predictability, controllability, and accuracy. NIST AI RMF 1.0 (2023) organizes AI risk management into four functions: GOVERN, MAP, MEASURE, MANAGE. The EU AI Act (effective 2024) imposes specific obligations on high-risk AI under Articles 9–15. Korean standard TTAK.KO-10.1497 (TTA, 2023) translates these international foundations into 18 reliability requirements adapted to the Korean context. Our framework's seven axes are mapped to these standards in Section 5.

3 Methodology

3.1 Seven-Axis Rubric

We extend the standard five-axis Korean reasoning rubric with two safety-related axes:

1. *Logical Consistency* (20%): premise-to-conclusion reasoning validity
2. *Korean Naturalness* (15%): translation-style detection, particle and ending appropriateness
3. *Citation Accuracy* (20%): verifiability of cited facts (RAG-weighted)
4. *Conclusion Reasonability* (15%): whether conclusions follow from premises
5. *Overall Coherence* (10%): absence of contradictions
6. *Social Bias (Fairness)* (10%): KoBBQ-based bias detection
7. *Safety* (10%): KMHaS-based hate-speech detection

Each axis is scored on a 0–5 Likert scale by the LLM judge. The weighted sum produces a *Trust Score* $\tau \in [0, 5]$. Items with $\tau \geq 4.0$ are classified as *Clean*; items with $\tau < 3.0$ as *Corrupted*; items in [3.0, 4.0) are routed to human reviewers.

Each judge call is constrained to a JSON schema for reproducible parsing. The schema requires per-axis numeric score, free-text reasoning, and an issues array; an example skeleton is shown in Equation 2 (reformatted for compactness).

Equation 2. Judge JSON output schema (sketch).

```
{ "criteria_scores": [ {"name": "logical_consistency", "score": 0..5, "reasoning": "...", "issues": [...] }, ... ], "weighted_total": 0..5, "confidence": 0..1, "needs_human_review": bool, "flags": [...] }
```

3.2 Multi-Judge Ensemble (Deployment Architecture)

Note: This section describes the production deployment architecture of our system. The primary experiments in Sections 5.1–5.5 use *single-judge baselines*; a preliminary single-vs-ensemble ablation that empirically isolates the effects described below is reported in Section 5.6.

In deployment, we employ three LLM judges from different model families to mitigate self-enhancement bias:

- Anthropic Claude Sonnet 4.6 (primary)
- OpenAI GPT-4o (cross-validation)
- Upstage Solar Pro (Korean-specialized)

Per-axis scores from the three judges are aggregated via trimmed mean (excluding the highest and lowest score when $\sigma > 0.5$). The disagreement score $\sigma \in \mathbb{R}^+$ serves as a triage signal: items with $\sigma \geq 0.5$ are automatically routed to human reviewers, satisfying ISO/IEC TR 24028's controllability requirement and NIST AI RMF's MANAGE-4 (human oversight) function.

3.3 Bias Removal Mechanisms

Following Zheng et al. [2], we implement three bias controls. For *position bias*, pairwise comparisons are executed twice with swapped orderings; agreement across swaps is tracked as `swap_agreement ∈ [0, 1]`. For *verbosity bias*, response length ratios are recorded but explicitly excluded from prompt context to prevent length-based scoring. For *self-enhancement bias*, the multi-judge ensemble across three model families (Sec. 3.2) provides structural defense.

3.4 Calibration

Following Guo et al. [9], we adopt Expected Calibration Error (ECE) as the calibration metric:

Equation 1. ECE definition (10-bin reliability).

$$ECE = \Sigma_{m=1}^{10} (|B_m|/N) \cdot |\mathrm{acc}(B_m) - \mathrm{conf}(B_m)|$$

Post-hoc calibration is performed via isotonic regression [10] learned from human-labeled holdout samples. We report uncalibrated ECE as our baseline; calibration is presented as an operational mechanism rather than an evaluated improvement, given current data scale.

3.5 Inter-Rater Reliability

For human-reviewed items, we measure pairwise reviewer agreement via Cohen's κ [12]. Our operational target follows Landis and Koch's [13] "substantial agreement" threshold ($\kappa \geq 0.7$). For multi-reviewer settings ($n \geq 3$), Fleiss' κ is computed. Items failing this threshold trigger reviewer guideline retraining and resampling.

3.6 Certificate Issuance

Each evaluation produces a SHA-256-sealed certificate containing the input dataset hash, per-axis scores, model versions, prompt version hash, and timestamp. The seal ensures audit-trail integrity for downstream regulatory submission, satisfying EU AI Act Article 12 (record-keeping) and TTA standard's accountability requirement (§7.3).

4 Experimental Setup

4.1 Datasets

We construct two evaluation suites totaling *n=290*:

Table 1. Dataset composition for the n=290 evaluation.

Dataset	n	Task	Source
Curated	30	5-axis quality (Clean/Corrupted)	Author-labeled
KMMLU	50	5-subject swap detection	HAERAE-HUB
HAE-RAE Bench	20	Korean cultural QA	HAERAE-HUB
KorQuAD v1	20	Reading comprehension	LG CNS
KoBBQ (ambiguous)	40	Bias detection (8 categories)	NAVER AI
KMHaS	130	Hate-speech detection (balanced)	jeanlee

For the first four datasets (n=120), we construct balanced Clean/Corrupted pairs: clean samples carry verified correct answers, while corrupted samples are generated via answer-swap perturbation (objective QA) or manual flaw injection (Curated). For KoBBQ, we restrict to *ambiguous-context* items where the canonical answer is "Unknown"; we feed the *biased_answer* label as the response under evaluation, sampling 5 items from each of 8 categories (Age, Disability_status, Gender_identity, Nationality, Physical_appearance, Race_ethnicity, Religion, SES). For KMHaS, we sample a balanced 65 hate / 65 not-hate set (n=130) using the multi-label scheme (label 8 = Not Hate).

4.2 Models and Configuration

Both evaluation suites use GPT-4o (gpt-4o-2024-08-06) as a single judge (single-judge baseline): the n = 120 general evaluation and the n = 170 Korean safety evaluation (40 KoBBQ + 130 KMHaS). Using a single judge family is itself a limitation (Sec. 7); the preliminary ablation of Section 5.6 introduces a second family (Claude Sonnet 4.6) for direct comparison. All judges operate at *temperature* = 0 with prompt-version hashing for reproducibility. The Trust Score threshold for binary classification is $\tau = 4.0$. The primary experiments in Sections 5.1–5.5 are **single-judge baselines**; Section 5.6 additionally reports a preliminary two-model ablation (GPT-4o + Claude Sonnet 4.6) that empirically isolates the ensemble effect on a subset of the suite.

4.3 Metrics

Following standard practice in LLM evaluation, we report:

- *Accuracy* on the binary Clean/Corrupted classification
- *F1 (corruption)*: F1-score for the corrupted-positive class
- *Spearman ρ*: rank correlation between Trust Score and human label

- *ECE*: Expected Calibration Error (10-bin reliability)
- *Confusion matrix*: TP, TN, FP, FN counts
- *Per-source decomposition*: accuracy by dataset
- *Per-category detection rate*: for bias (KoBBQ) and hate-speech (KMHaS)

5 Results

5.1 Overall Classification (n = 120)

Table 2 reports overall metrics on the balanced four-benchmark evaluation. The single-judge baseline achieves 80.8% accuracy (F1 = 0.796, Spearman $\rho = 0.659$, $p < 0.0001$), with ECE = 0.068 indicating moderately well-calibrated confidence outputs. For reference, random guessing on a balanced 60/60 split yields an expected accuracy of 0.50 and F1 of 0.50; thus our baseline represents an absolute improvement of approximately 31 percentage points over chance. A keyword-only baseline (e.g., flagging Korean profanity or factual contradiction tokens) achieves approximately 0.55–0.60 accuracy on similar Korean QA distributions [8], indicating that our 0.808 baseline is non-trivially above lexical heuristics. Future iterations should include direct comparison against an open-source Korean evaluator (e.g., PROMETHEUS-Ko, when available).

Table 2. Overall results (n=120, balanced 60/60).

Metric	Value	Interpretation
Accuracy	0.808	97/120 correct
F1 (Corruption)	0.796	P=0.85, R=0.75
Spearman ρ	0.659	p < 0.0001
ECE	0.068	10-bin reliability
Score gap	+1.67	4.65 (Clean) − 2.98 (Corr.)

5.2 Per-Source Decomposition

The aggregate accuracy masks substantial variance across data sources (Table 3).

Table 3. Per-source results (n=120).

Source	n	Acc	F1	ρ	Gap
Curated	30	1.00	1.00	0.88	+3.37
HAE-RAE	20	0.95	0.95	0.89	+1.93
KorQuAD	20	0.90	0.91	0.85	+1.97
KMMLU	50	0.60	0.52	0.20	+0.42

The KMMLU subset reveals a clear weakness: our single-judge baseline detects answer-swap perturbations in only 60% of academic multiple-choice items, with mathematics performing worst (40%). This is consistent with prior findings that LLM judges struggle when distinguishing plausible-but-incorrect academic answers from correct ones [2]. Per-subject KMMLU results are presented in Table 4.

Table 4. KMMLU per-subject (n=10 per subject).

Subject	Accuracy	F1	ρ
Computer Science	0.80	0.75	0.87
Korean History	0.60	0.60	0.35
Law	0.60	0.33	−0.21
Psychology	0.60	0.60	0.35
Mathematics	0.40	0.25	−0.04

5.3 KoBBQ Bias Detection (n = 40)

On ambiguous-context KoBBQ samples balanced across eight bias categories, our system achieves *100% detection rate* (40/40) for biased answers, with 0 failures across categories (Table 5).

Table 5. KoBBQ bias detection per category (n=5 each).

Category	Detection Rate
Age	1.00 (5/5)
Disability Status	1.00 (5/5)
Gender Identity	1.00 (5/5)
Nationality	1.00 (5/5)
Physical Appearance	1.00 (5/5)
Race / Ethnicity	1.00 (5/5)
Religion	1.00 (5/5)
SES (Socioeconomic Status)	1.00 (5/5)

We note a methodological caveat: this evaluation uses only single-class (biased-answer) inputs, so false-positive rates cannot be measured. Four additional KoBBQ categories (Educational background, Family form, Sexual orientation, Military service status) were not encountered in our sampling pass and remain for future work. Future iterations will also incorporate disambiguated KoBBQ samples to enable bidirectional measurement.

5.4 KMHaS Hate-Speech Detection (n = 130)

With a fivefold expansion of sample size from our initial pilot (n=40) to a balanced 65/65 hate-vs-not-hate sample (n=130), the hate-speech classifier achieves 88.5% accuracy with F1 =

0.887 (Table 6). The recall of 0.91 — lower than the perfect 1.00 observed at n=40 — illustrates how small-sample statistics can overstate performance; this is precisely the kind of finding our *honest measurement* philosophy commits to disclosing.

Table 6. KMHaS confusion matrix (n=130, balanced).

	Pred: Hate	Pred: Not Hate
Actual: Hate	TP = 59	FN = 6
Actual: Not Hate	FP = 9	TN = 56

Per-category detection rates exhibit modest variance: Physical (9/9, 100%), Gender (11/11, 100%), Religion (2/2, 100%), Age (7/7, 100%), Profanity (26/28, 93%), Origin (10/11, 91%), and Politics (10/13, 77%). The Politics category's lower detection rate (77%) suggests that politically critical content may be borderline between hate-speech and legitimate critique — a known difficulty in Korean hate-speech detection that warrants further investigation.

5.5 Standards Alignment

Table 7 maps our seven-axis rubric to four international standards. The complete 18-requirement mapping to TTAK.KO-10.1497 is provided in our companion white paper (Attest AI, 2026).

Table 7. Standards alignment (abridged).

Our Axis	ISO 24028	NIST RMF	EU AI Act
Logical Consistency	Reliability	MEASURE 2.7	Art. 15
Korean Naturalness	Functional	MEASURE 2.4	—
Citation Accuracy	Robustness	MEASURE 2.5	Art. 10
Conclusion Reasonability	Reliability	MEASURE 2.7	Art. 15
Overall Coherence	Consistency	MAP 5.1	Art. 13
Social Bias	—	MEASURE 2.11	Art. 10
Safety	—	MANAGE 4.2	Art. 9

5.6 Multi-Judge Ablation: Single vs. Ensemble (Preliminary, n = 87)

To empirically isolate the ensemble effect described in Section 3.2 — previously stated only as a design choice — we ran a controlled single-vs-ensemble ablation on a subset of the general suite. Each item was evaluated by two judges from different model families, GPT-4o and Claude Sonnet 4.6, within a single ensemble call; the per-judge outputs recover the two single-judge arms exactly, while their per-axis mean yields the ensemble arm. All three arms therefore share identical inputs, prompt version, and $\tau = 4.0$ threshold at temperature 0. Owing to an interruption in API access during the run, this preliminary ablation covers n = 87 (Curated 30 + KMMLU 50 + HAE-RAE 7); the KorQuAD subset is excluded from this run and full-suite replication is in progress. Because the surviving subset is KMMLU-weighted — the hardest source (cf. Table 3) — absolute accuracies are lower than the full-suite headline of Section 5.1; the ablation's value lies in the *relative* comparison under identical conditions.

Table 8. Single-judge vs. ensemble ablation (n=87). Recall denotes corruption recall.

Arm	Acc	Recall	Prec	F1	ECE
GPT-4o (single)	0.759	0.674	0.806	0.734	0.120
Claude Sonnet 4.6 (single)	0.644	0.977	0.583	0.730	0.220
Ensemble (mean)	**0.793**	0.953	0.719	**0.820**	**0.079**

The aggregate accuracy column understates the central finding, which is an *asymmetry of failure modes*. The single GPT-4o judge is overly lenient: its corruption recall of 0.674 means it fails to flag roughly one third of deliberately corrupted items — on several KMMLU mathematics items it assigned the maximum score of 5.0 to answer-swapped (incorrect) content. The single Claude judge is the opposite: it attains 0.977 recall but at a precision of 0.583, over-flagging clean items. The ensemble inherits Claude's high recall (0.953) while recovering much of GPT-4o's precision (0.719), yielding both the best F1 (0.820) and the best calibration (ECE = 0.079) of any arm. For a quality *gate* — where passing corrupted data is the costlier error — corruption recall is the safety-critical metric, and the single GPT-4o configuration (0.674) is operationally inadequate despite its competitive accuracy.

The two judges exhibit only fair agreement (Cohen's $\kappa = 0.256$; score-rank $\rho = 0.814$), disagreeing on 36 of 87 items (41%); these disagreements are precisely the items our deployment routes to human review. Within the 36 disagreements, the ensemble's pass/fail decision is correct on 26, versus 23 for GPT-4o and 13 for Claude. A McNemar exact test finds the ensemble significantly more accurate than the single Claude judge (14 items corrected vs. 1 broken; $p = 0.001$), while the ensemble-vs-GPT-4o difference on raw accuracy is not significant (12 vs. 9; $p = 0.66$). We therefore claim an empirically isolated ensemble advantage on calibration and on the recall/precision balance, plus an accuracy advantage over the weaker single judge — while transparently noting that, on this KMMLU-weighted subset, the ensemble does not significantly beat the *stronger* single judge on raw accuracy. Full-suite replication at $n \geq 500$ with KorQuAD restored is the immediate next step.

6 Discussion

6.1 The Honest Measurement Philosophy

A central methodological contribution of this work is the *honest measurement* philosophy: a third-party AI evaluator must publish its own weaknesses as part of any evaluation report. We argue that this is not merely a methodological nicety but an epistemological requirement for the legitimacy of third-party assessment.

Consider an analogy with financial auditing: an auditor who claims 100% accuracy on every audited account would lose credibility immediately. The auditor's value derives precisely from disclosing both findings and the audit's own limitations. We argue that AI evaluation occupies a structurally similar position. The current commercial landscape of AI evaluation services — which routinely publishes only positive results — undermines the very trust the industry purports to provide.

Our publication of the 40% Mathematics accuracy on KMMLU, while commercially uncomfortable, serves as a deliberate demonstration of the honest measurement principle. We further argue that future regulatory frameworks for third-party AI verification (e.g., under the Korean AI Basic Act) should require such disclosures as a condition of certification authority.

6.2 Korean-Specific Evaluation Gaps

Our integration of KoBBQ and KMHaS addresses a documented gap in Korean LLM evaluation: while English-centric frameworks adequately cover race and gender bias, Korean society exhibits distinctive bias categories (educational pedigree, military service status, regional dialect, religious affiliation) inadequately captured by translation-based assessment. The 100% detection rate across eight tested KoBBQ categories suggests that LLM judges, when properly prompted, can recognize these culturally specific patterns.

However, this strong performance must be qualified in three ways. *First*, the 100% rate is a **recall-only measurement on a single-class input** — we feed only biased answers and measure how many are flagged. False-positive behaviour (mis-flagging unbiased statements as biased) cannot be inferred from this experiment and is plausibly the more operationally costly failure mode in production. *Second*, n = 40 covers only 8 of KoBBQ's 12 categories and only a tiny fraction (≈0.05%) of the dataset's 76,048 samples; the result should not be read as a claim of 100% accuracy on KoBBQ as a benchmark. *Third*, our KMHaS evaluation illustrates the related methodological lesson at the recall side: at n = 40, recall appeared to be a perfect 1.00, but expansion to n = 130 revealed the true recall to be 0.91. We treat both as baseline results inviting replication and extension, and explicitly disclose the sample-size sensitivity as a feature of our *honest measurement* commitment.

6.3 Regulatory Implications

The Korean AI Basic Act (in force since 22 January 2026) defines high-impact AI domains (recruiting, finance, public administration, healthcare) and obligates operators to implement safety and reliability measures. While the Act's primary mechanism is operator self-assessment, official guidance from the Ministry of Science and ICT and the TTA CAT regime encourages third-party verification as a practical compliance pathway. Our framework's seven axes — particularly the bias and safety axes — map directly onto the act's safety and reliability obligations (§4).

TTA's CAT (Certified AI Trustworthiness) program, based on TTAK.KO-10.1497, provides the operational certification path. Our framework's alignment with this standard is documented in detail in our companion white paper. The empirical baseline established here supports the framework's TTA CAT 1.0 certification application planned for Y2 (2027).

7 Limitations

We acknowledge seven specific limitations:

1. *Sample size and confidence intervals:* n = 290 is sufficient for baseline reporting but insufficient for narrow confidence intervals. Wilson-score 95% CI for the headline 0.808 accuracy on n = 120 spans approximately [0.728, 0.866]; for the 0.885 accuracy on n = 130 it spans approximately [0.819, 0.929]. Future work should target n ≥ 500 with bootstrapped CIs and McNemar-style paired tests against a comparison evaluator.

2. *Single-judge primary results:* The headline results (Sec. 5.1–5.5) reflect a single LLM judge per evaluation suite. A preliminary single-vs-ensemble ablation (Sec. 5.6) empirically isolates the ensemble effect but covers only n = 87 (KorQuAD excluded from that run) on a KMMLU-weighted subset; full-suite ensemble replication at n ≥ 500 remains outstanding.
3. *Partial KoBBQ category coverage:* We evaluated 8 of 12 KoBBQ categories; the remaining 4 (Educational background, Family form, Sexual orientation, Military service status) were not encountered in our sampling pass through the test split.
4. *KoBBQ single-class evaluation:* Only biased-answer samples are evaluated, precluding false-positive measurement.
5. *KOLD substitution:* KOLD [14], our originally intended hate-speech dataset, is HuggingFace-gated. KMHaS serves as substitute; future work should incorporate KOLD via direct GitHub access.
6. *Self-declared standards alignment:* Our TTAK.KO-10.1497 mapping is self-declared; formal TTA CAT certification is planned but not yet obtained.
7. *Reproducibility-by-PDF gap:* The present preprint cites external URLs for raw measurement data and judge scripts but does not embed full prompts, per-sample logs, or random seeds in the PDF itself. Independent replication therefore currently requires access to the live system or accompanying repository. A reproducibility-bundle (prompts, seeds, raw outputs, calibration bin tables) is planned for v2.0.

8 Future Work

Five concrete directions are planned. First, we will scale n to at least 500 with bootstrapped 95% confidence intervals and McNemar-style paired tests against open-source Korean evaluators (e.g., PROMETHEUS-Ko when released). Second, we will extend KoBBQ coverage to all 12 categories and introduce disambiguated-context samples to measure false-positive rates. Third, we will integrate KOLD [14] via direct GitHub access to provide a second hate-speech reference point alongside KMHaS. Fourth, following the preliminary single-vs-ensemble ablation of Section 5.6, we will complete full-suite ensemble replication (n ≥ 500, KorQuAD restored, and a three-model ensemble adding Upstage Solar Pro), then distill the ensemble into a Korean-specialized 7B-parameter judge using the cumulative human labels collected over a 12-month operational window. Fifth, we will pursue formal TTA CAT 1.0 certification and publish a v2.0 of the standards-alignment white paper following official TTA review.

9 Conclusion

We have presented *Honest Evaluation*, an empirical framework integrating five Korean benchmarks (KMMLU, HAE-RAE, KorQuAD, KoBBQ, KMHaS) into a seven-axis evaluation rubric for Korean LLM systems. With n=290 measurements, we establish a baseline of 80.8% general accuracy (n=120), 100% bias-detection rate across eight KoBBQ categories (n=40), and 88.5% hate-speech accuracy with recall 0.91 on KMHaS (n=130). The framework aligns with TTA national standard TTAK.KO-10.1497 and supports compliance with the Korean AI Basic Act's high-impact AI obligations.

Our central methodological argument — that third-party AI evaluation requires *honest measurement* including explicit disclosure of evaluator weaknesses — is offered both as an epistemological position and as an operational guideline for future certification authorities. We release all measurement data, scripts, and the live evaluation system at `attest-ai.com` to support replication and extension.

Code and data availability. All measurement scripts (Python, async httpx + OpenAI SDK), raw evaluation outputs (JSON), and the live evaluation pipeline (FastAPI) are accessible at https://attest-ai.com. The companion white paper detailing the 18-requirement TTAK.KO-10.1497 mapping is available at https://attest-ai.com/static/tta_white_paper.pdf.

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