# Human-centric prompt evaluation

Gary Condon, Technological University Dublin

MSc in Computing in Human Centered Artificial Intelligence

Abstract. This research develops an integrated framework for evaluating Large Language Model (LLM) prompts, combining technical metrics with human-centric assessments. The framework implements quantifiable metrics, workflow checkpoints, and user feedback loops, creating a balanced methodology for assessing prompts in complex Al systems where human oversight is crucial.

### **INTRODUCTION**

While technical frameworks exist for human-centric evaluation, prompt assessment remains understudied. This gap has become increasingly critical as global investment in artificial intelligence approaches \$749 billion by 2028[1], with agentic Al representing a significant portion. Complex multi-stage agentic workflows will likely amplify biases, user concerns and environmental impacts, necessitating frameworks that evaluate both technical and humanaspects of prompts.This centered research investigates approaches to integrate human-centered concerns into prompt quality evaluations, leverageable in both direct user-LLM interactions and agentic workflows.

## LITERATURE REVIEW

In their investigation of bias in large generative models, David Esiobu (et al.) prompt-based different found that datasets can be used to measure biases across different LLMs[2]. In Jwala Dhamala's 2021 paper[3], they proposed methodologies for measuring bias and toxicity in outputs from LLMs which may steer the direction of bias evaluation for this research. In their 2024 work titled 'The Price of Prompting', Erik Johannes investigated Husom (et al.), environmental impact of prompt length and complexity.

# RESEARCH METHODOLOGY

The research will develop a humancentric prompt evaluation framework through two phases: first identifying critical metrics through literature review, then developing an integrated framework with quantifiable metrics and workflow checkpoints for systematic improvement.

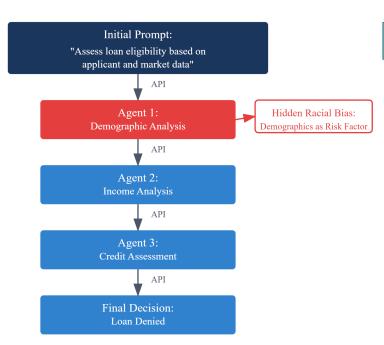


Fig. 1. An illustration of a hypothetical Agentic multistage workflow. In this example, you can see that the loan approval determination might be made based on a biased decision, but the decision-making process is not surfaced to the user.

### **HUMAN CENTRED FOCUS**

The focus on reducing bias and ensuring user safety aligns with the United Nations Sustainable Development Goal 10 (Al inclusivity), while reducing the environmental impact of LLM interactions through identification of complex and lengthy prompting aligns with SDG 12 (Sustainable consumption). This research also aligns with the European Union's ALTAI principles of fairness.







# **EXISTING FRAMEWORKS**

There are a number of existing frameworks that provide feedback on prompt technical accuracy. This research aims to learn from and supplement these frameworks with human-centric focus. These include:

- EvalLM—iterative prompt refinement
- PromptEval—scaled prompt evaluation
- ChainForge –visual feedback loops

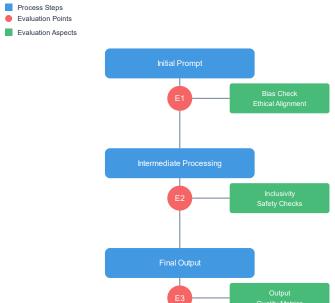


Fig. 2. Using the ChainForge framework to evaluate bias across multiple LLMs based on the quality of the user's prompting.

# DATASET CANDIDATES

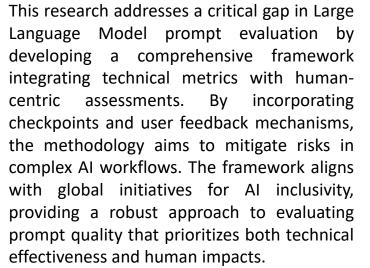
HolisticBias[4] is a dataset of 600 identity terms across 13 demographic categories, collaboratively developed with community members to reflect authentic self-identification using diverse descriptors. AdvPromptSet[5], created by Meta Research, comprises 200K prompts with varying toxicity levels across 24+ demographic groups, incorporating integrity and demographic metadata to evaluate AI system responses.

Evaluation Framework for LLM Workflow Steps



**Fig. 3.** A sample Agentic workflow with proposed human-centered check-points to evaluate prompts for biased outcomes

# **CONCLUSIONS**



### References.

[1] UiPath Report Reveals Agentic Al is Driving Investment to Tackle More Complex Business Workflows. (n.d.). <u>Https://lr.Uipath.Com/News/Detail/376/Uipath-Report-Reveals-Agentic-Ai-Is-Driving-Investment-to-Tackle-More-Complex-Business-</u>

<u>Workflows?Utm\_source=chatgpt.Com.</u>
[2] ROBBIE: Robust Bias Evaluation of Large Generative Language Models. (n.d.) https://arxiv.org/abs/2311.18140

[3] Dhamala, J., Sun, T., Kumar, V., Krishna, S., Pruksachatkun, Y., Chang, K. W., & Gupta, R. (2021). BOLD: Dataset and metrics for measuring biases in open-ended language generation. FAccT 2021 - Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency, 862–872. https://doi.org/10.1145/3442188.3445924

[4]Husom, E. J., Goknil, A., Shar, L. K., & Sen, S. (2024). The Price of Prompting: Profiling Energy Use in Large Language Models Inference.

Energy Use in Large Language Models Inference. [5] fairnlp/holistic-bias · Datasets at Hugging Face. (n.d.).

[5] fairnlp/holistic-bias · Datasets at Hugging Face. (n.c. Https://Huggingface.Co/Datasets/Fairnlp/Holistic-Bias.

 $\label{lem:constraint} \begin{tabular}{ll} [6] Responsible NLP/AdvPromptSet/README.md at main \cdot facebook research/Responsible NLP/Tree/Main/AdvPromptSet (n.d.). \\ \begin{tabular}{ll} Https://Github.Com/Facebook research/Responsible NLP/Tree/M$ 



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