Now You See Me: Using Generative AI to Drive Engagement with Data Visualizations

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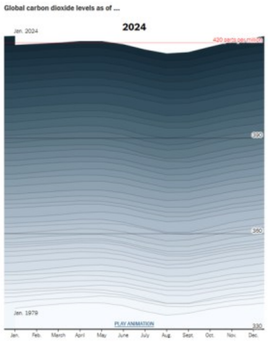

Visualization analyzed
↓
Comment received
↓
Context interpreted
↓
AI response generated

Comment: *"Climate change is baked into the system."*

Response: *"While some CO_2 lingers, current levels exceed 420 ppm, impacting today's climate."*

Figure 1: *New York Times* chart [4] (left) is analyzed through the agent workflow (middle), which reframes an audience comment (right) using current CO_2 levels (420 ppm).

Abstract

While data visualizations can drive evidence-based discussion, audience comments often overlook or misinterpret their content. This paper introduces a lightweight proof-of-concept AI agent, powered by a multimodal generative model that analyzes data visualizations and audience responses in online discussions. The agent detects whether comments reference the visualization, identifies potential misinterpretations, and compares interpretations to the underlying data. It then generates tailored responses to encourage more accurate and visualization-centered engagement. This approach offers a scalable way to improve discussion quality and strengthen the connection between audiences and the visual evidence presented.

Index terms: Generative AI, agent-augmented visualization, audience engagement, online discussions.

1 Introduction

Data visualizations are widely recognized as an effective way to communicate stories to the public [16]. Prior work has shown that their design choices can influence audience engagement and interpretation [8]. Comments on news stories containing data visualizations can provide valuable insights into civic issues [9,14,17]. However, analyses of comment sections show that only a fraction of comments address the visualizations directly or engage with the quantitative data they present [9,14]. This raises a key question: how can engagement with data visualizations be encouraged and sustained in online discussions?

One promising way to address this engagement gap is to detect, in real-time, patterns of audience engagement with data visualizations. This capability lays the groundwork for designing interventions that support audiences in interpreting and applying quantitative information more effectively. Such automation reduces reliance on manual coding, which is labor-intensive, prone to bias, and impractical for large-scale or time-sensitive analysis [11,14].

The development of chart detection methods, LLMs, and AI agents provides a powerful environment for better understanding and shaping audience behavior. Together, these tools can provide scalable, data-driven insights into how visualization design choices influence engagement and what barriers limit their effective use. They can also generate personalized prompts that encourage audiences to engage more directly with the numbers, trends, and comparisons presented in the visualization. For example, Figure 1 illustrates a case from the *New York Times* [4], in which a climate change comment expressed a fatalistic claim: *"Climate change is baked into the system."* The AI agent, by analyzing the chart, reframed this claim with a data-grounded response: *"While some CO_2 lingers, the first chart reveals current levels exceeding 420 ppm, impacting today's climate."* In this way, audiences are guided from deterministic or vague statements

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toward evidence-based reasoning, fostering deeper exploration and more expansive discussions.

This paper reviews emerging computational approaches that collectively support interactive systems aimed at enhancing audience engagement with data visualizations. We then demonstrate how these approaches can be implemented in real-world settings, propose strategies to address the identified challenges, and illustrate their contributions across multiple domains.

2 LITERATURE REVIEW

Studies on data-driven storytelling indicate that only a subset of the audience engages with data visualizations [9,10,14]. Because visualizations vary in type, design, topic, and audience, identifying the barriers to effective engagement remains challenging. Recent technological developments enable automatic, large-scale exploration of the relationships between visualization design choices, audience characteristics, and engagement outcomes. Advances in information extraction from visualizations, combined with LLMs, offer new opportunities to analyze audience responses at scale and with greater effectiveness.

Chart Detection. Several solutions for chart detection, including Gemini and ChatGPT, have recently emerged. While these systems are able to identify and describe visualizations, research indicates that the visualization literacy of LLMs remains largely dependent on pre-existing knowledge, and they often struggle to apply information from visualizations when confronted with new cases [7]. These limitations may be mitigated through better training data, structured extraction methods, or domain-specific context.

Chart Interpretation. Studies on LLMs extracting insights from visualizations have found that they sometimes produce hallucinations, omit key information, and misinterpret ambiguous or misleading visual encodings [3,12]. Moreover, LLMs often generate different types of insights from charts than humans, and their responses do not consistently reflect the systematic sensitivity to design choices observed in human interpretations [18]. In addition, while LLMs may process information differently from humans and thereby reduce certain cognitive biases; however, they lack the adaptive heuristics that often serve as efficient strategies in human decision-making [2]. Some of these issues may be mitigated through improved prompt design, the inclusion of contextual information, or structured interaction strategies.

Engaging the audience. Several studies have examined the effects of visualization assistance on the audience [6,19]. In a controlled study using several chart types [6], it was found that LLM assistance, while preferred by audiences with low visualization literacy, led to a reduction in direct engagement with the visualizations and resulted in fewer reported insights. Another study [5] found that expert audiences tend to adopt a narrow, focused attention strategy, whereas novices display broader and more exploratory viewing patterns.

Together, these studies highlight both the opportunities and the limitations of applying LLMs and AI assistance in visualization contexts, underscoring the need for adaptive approaches that account for task complexity, design choices, and audience expertise.

3 METHODOLOGY

Our approach examines online discussions, where responses reflect spontaneous and authentic engagement with visualizations. To leverage this setting, we developed a proof-of-concept agent powered by Gemini, Google's multimodal LLM, chosen for its ability to integrate visual and textual understanding while producing semantically coherent responses. The agent is designed with a modular architecture that enables it to serve a dual role: providing scalable insights into how visualizations are interpreted, and directly engaging with audiences in real time to address misinterpretations and support interpretation.

The agent operates through an analysis pipeline. First, the visualization analysis stage detects visual elements such as graphical objects, titles, captions, and surrounding text. Second, the data extraction stage interprets the data in the visualization, identifying key values, trends, and comparisons. Finally, the response linking stage connects the extracted data to the visualization's content and structure, assessing whether audience comments introduce relevant insights, novel framings, or possible misinterpretations.

Once the analysis is complete, the agent can produce tailored responses that provide supporting evidence, highlight trends that contradict a statement, or invite reconsideration based on the visualization's data. Alternatively, the agent may determine that the discussion requires no intervention and refrain from responding. The responses are configured along two independent dimensions:

1. Delivery Mode – either *ephemeral on-screen messages* that disappear after viewing, minimizing disruption to the ongoing discussion, or *private feedback* that allows the commenter to reflect without altering the visible conversation.

2. Target Location – either *top-level comments* to spark new discussion or *specific replies* within ongoing exchanges to strengthen argumentation.

Both dimensions are adjustable by journalists based on editorial guidelines and prior experience with the commenting community, allowing the agent to be tailored for maximum engagement and relevance.

To generate responses, the agent is guided by an instruction prompt that integrates visualization analysis with conversational strategies. The prompt directs the agent to first check whether the comment misinterprets or conflicts with the data, and if so, to gently correct the misunderstanding by pointing to specific numbers or trends. If the comment is consistent with the data, the agent instead provides a new, non-obvious insight or suggestion derived from the visualization, nudging the user toward deeper engagement. In both cases, the response is grounded in the visualization, avoids repetition, and is phrased in a concise, supportive, and sometimes lightly humorous way to sustain audience interest. As illustrated in the introduction, this approach moves from detecting alignment or misalignment to generating a visualization-centered prompt that supports engagement. Full prompt is provided in the supplementary materials.

4 Potential Applications

The proposed agent can be deployed across online news platforms, educational forums, and civic discussion spaces to promote accurate, visualization-centered engagement. For journalists, it can function as a real-time moderation and engagement tool [13], delivering prompts either as ephemeral on-screen notes or as private messages. For educators, it can guide students' exploration of graphs, such as in the American Statistical Association and *New York Times* Learning Network's *What's Going on in This Graph?* [1,15], by helping them move from initial observations toward evidence-based reasoning. For researchers, it can link misinterpretation patterns to specific visual design choices, providing actionable feedback for creating graphics that are more resistant to misunderstanding and better aligned with audience cognition.

5 Limitations and Future Work

The current implementation is proof-of-concept and has not yet undergone empirical evaluation in live settings. Its effectiveness in changing audience behavior, the potential for unintended bias in generated responses, and its adaptability across visualization types remain open questions.

From a technical standpoint, acquiring and interpreting visualizations presented notable challenges. Attempts to scrape HTML for direct extraction often failed due to slow rendering or bot protection, which required the use of browser-rendered screenshots instead. This alternative introduced two limitations: first, the AI model sometimes struggled to detect relevant charts when multiple visualizations or graphic objects appeared on the same page; second, static screenshots could not capture interactive elements such as tooltips, filters, or animations, potentially omitting critical information when comparing extracted data to audience responses.

Future work will evaluate the agent's ability to extract information from visualizations using multiple model comparisons and controlled experiments to measure its impact on engagement. Prompting strategies will also be refined to maximize effectiveness, with adjustments such as audience-specific messaging, humor, and selective intervention for clear misinterpretations.

6 Conclusion

This work introduces an AI agent designed to drive online discussions toward deeper and more accurate engagement with data visualizations. By detecting references, identifying misinterpretations, and generating targeted responses, the agent provides a scalable approach to bridging the gap between visualization design and audience understanding. While still at the proof-of-concept stage, the system offers a foundation for future empirical studies and practical applications in journalism, education, and civic discourse, with adaptable delivery modes that can be tuned to fit the needs and norms of different discussion spaces**.**

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Supplemental Materials

All supplemental materials are available on OSF at https://osf.io/7bjdq, released under a CC BY 4.0 license. They include:

1. The Python implementation of the AI agent, including its full prompt.
2. Screenshot image.
3. Audience comments.
4. AI agent output; and
5. The full version of this paper.

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