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Signs of Intelligence: Trust in Generative Artificial Intelligence for Conservation Messaging

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ABSTRACT
The growing integration of Generative Artificial Intelligence (AI) across disciplines presents new opportunities for innovation, yet its adoption in the field of conservation education remains limited. Part of the lack of adoption stems from a potential trust deficit with the use of AI. We applied a novel AI design framework to the development of conservation-oriented signage at McCroskey State Park in Idaho to explore how AI can support communication and engagement in under-resourced natural areas. Through a human interaction-facilitated process using Retrieval Augmented Generation, we examined the trust local organizations representatives had in the use of AI technologies pre- and post-signage creation. Results indicated increased rational trust and reduced lack of affinitive trust (intimidation), highlighting the importance of transparency and oversight in conservation content creation. By showcasing this process that employed AI in conservation messaging, we offer budget-constrained conservation agencies a practical approach to leverage emerging technologies for environmental education and outreach, while engendering greater trust in new technologies.

INTRODUCTION
In 2022, the adoption of Generative Artificial Intelligence (AI) swept the world with wide-ranging concerns, from job stability and education standards to environmental impacts. Global alarm is weighed against AI's transformative potential. For example, AI integration in the energy sector may assist in addressing climate change when accompanied by robust policy guardrails (Cowls et al. 2023). Pandey et al.'s (2023) bibliometric analysis identifies nearly 50 years of research documenting how machine learning, big data, and AI increased efficiency in natural resource contexts, ranging from groundwater utilization to urban planning. AI's use in these global sustainability efforts raises the question of its potential within other environmental fields, such as conservation education.

As defined by the US Department of Agriculture (2014), "conservation" involves protecting, managing, and restoring natural environments. Yet national and global conservation efforts are costly and time-consuming; Deutz et al. (2020) estimated an annual funding gap of $598–824 billion (USD) for achieving global conservation targets. And, like conservation, education comes with its own costs, requiring time, funding, and expertise to be truly effective. In a political climate where financial investment in US public-sector parks (e.g., Barrett, Pitas, and Mowen 2017) and protected areas (e.g., Executive Order No. 14210, 2025) is rapidly waning, a need to explore financially viable mechanisms to continue conservation education is vital.

In parks and protected areas, conservation education through interpretation is widely recognized as effective for encouraging stewardship by inspiring care and responsibility (Manning 2022). According to Ham (2013: 8), "interpretation is a mission-based approach to communication aimed at provoking in audiences the discovery of personal meanings and the forging of personal connections with things, places, people, and concepts." Tilden (2007), often hailed as the father of park interpretation, famously stated, "through interpretation, understanding; through understanding, appreciation; through appreciation, protection," highlighting interpretation's role in conservation. Research supports this approach; Ballantyne et al. (2023) found that values-based interpretation improved environmental learning and pro-environmental behaviors, while Lu et al. (2016) showed that risk-benefit messaging increased visitor engagement with park staff on wildlife concerns. Encouraging pro-environmental behaviors is vital for protecting threatened ecosystems, making interpretation a key tool for conservation and stewardship.

Given the costs associated with conservation education and the potential for AI to assist in interpretive efforts, we sought evidence of how AI can assist in the development of stationary interpretive content. Specifically, we explored AI's utility in creating signage for one sample site, McCroskey State Park in Idaho, while also evaluating the trustworthiness of the AI-generated content among park stakeholders. While AI can aid in creating interpretive materials, a notable trust deficit exists with respect to AI-generated information (e.g., Jacovi et al. 2021). Therefore, it's essential to analyze this relationship to understand how AI can be reliably used for educational purposes. For McCroskey State Park, creating interpretive signs required accurate information about local species, park history, and other relevant topics. By collaborating with local agencies and park partners, we successfully gathered content to source in AI models and then assessed how much trust content providers placed in the AI-generated material. As Tilden (2007) stated, "gadgets do not supplant the personal contact; we accept them as valuable alternatives and supplements." In this study, we assessed the assumption that AI can be employed in supplementary ways to support conservation efforts, ultimately reducing time and costs, provided perceived quality is maintained.

LITERATURE REVIEW

AI

"Generative AI" refers to machine-learning systems that analyze vast amounts of data to generate responses based on user input. These models rely on information processing, logical reasoning, and mathematical algorithms to identify patterns in existing content—such as text, images, and videos—to create new, artificial outputs (Baidoo-anu and Owusu 2023). *Generative Pre-trained Transformers* (GPT) models, the language model underpinning systems like ChatGPT, process extensive datasets using natural language processing, enabling them to generate human-like responses.

AI's role in education is expanding, providing teachers with lesson strategies, professional development resources, and innovative learning techniques (e.g., Chiu 2023). Intelligent Tutoring Systems function as AI-driven tutors, offering personalized learning experiences (Holmes and Tuomi 2022). However, Large Language Models (LLMs) can generate misleading or incorrect outputs—often referred to as "AI hallucinations" or "confabulations"—when trained on incomplete or inaccurate data (Peng et al. 2023). This raises two key questions: How can AI enhance education beyond traditional classrooms, such as within parks and protected areas? And how can facilitated use of AI improve the trustworthiness of AI-generated knowledge?

Trust

The broad acceptance of AI relies on society to place trust in its application. Trust is often defined as "the willingness of a person to accept vulnerability to another party in the face of uncertainty" (Stern 2018). To *distrust* something is to assume there will be an undesirable or hurtful outcome, while a *lack of trust* is simply not having enough information to form a positive or negative expectation (Stern 2018). Spears et al. (2022) suggest that trust placed in an institution or agency is based on whether the individual believes there are shared goals and values. Multiple variables make up what is referred to as a "trust ecology" (Stern and Coleman 2015): (1) *dispositional trust*, (2) *affinitive trust*, (3) *rational trust*, and (4) *procedural trust*. These variables can help place contextual reasoning behind the trust placed between a trustor (an individual) and a trustee (a person, group, organization, etc.).

Dispositional trust is a baseline level of one's trust. This is dependent on the past experiences and culture of the trustor, and it highlights one's overall tendency to trust others. *Affinitive trust* is based on the relationship between the trustor and the trustee, representing an emotional connection. In reference to affinitive trust, Stern (2018: 104) simply states, "the more I like you personally, the more likely I am to trust you." *Rational trust* depends on what the trustor believes the predicted outcomes of the trustee's actions will be. By confidently predicting that the trustees' action will benefit the trustor, trust will be placed. *Procedural trust* (also referred to as *systems-*

based trust) can be defined as the trust placed in an entire system or a set of procedures or rules that are deemed "fair" by the trustor (Stern 2018). In sum, an understanding of trust ecology is especially important in fields that depend on public trust, such as conservation and education.

Interpretation

Interpretation plays a crucial role in fostering public care and consideration for natural and cultural resources. Ham (2013) describes interpretation as a mission-driven approach to communication that helps audiences form personal connections with landscapes, history, and concepts. Thoughtfully crafted interpretation can shape visitor attitudes by encouraging reflection and engagement. In addition to *personal interpretation*, where an individual interacts directly with a willing audience, another effective mechanism is known as *non-personal interpretation* (Hvenegaard et al. 2015), such as interpretive signage. Signs, visitor centers, and wayside exhibits not only connect visitors to the landscape but also help tell its stories. Additionally, Barros and Pickering (2017) highlight the role of signage in encouraging responsible behavior, such as staying on designated trails to protect vegetation.

Put differently, interpretive signs serve both educational and behavioral purposes. By fostering intellectual and emotional connections, they enhance visitor understanding of their surroundings but also shape corresponding actions. Research by Ismail (2008) found that interpretive signs at Penang National Park, Malaysia, successfully promoted environmental awareness, reducing littering and encouraging visitors to share conservation messages. Similarly, Hughes et al. (2009) observed that nearly 80% of visitors kept their pets leashed when prompted by signs, compared to just 60% without signage. While visitors often prefer in-person interactions with park rangers (Manning 2022), signs provide a cost-effective, accessible alternative, making them particularly valuable in remote locations like McCroskey State Park, which is situated in the Palouse ecoregion.

Palouse Prairie

The Palouse Prairie, spanning southeastern Washington and north-central Idaho, consists of rolling hills shaped by wind-deposited loess (Looney and Eigenbrode 2012). Once vast native grasslands, over 99% were converted to farmland in the 1800s, leaving behind a critically endangered ecosystem (Davis 2015). The few remaining prairie remnants support endangered species, such as Spalding's catchfly (*Silene spaldingii*) and the Palouse giant earthworm (*Driloleirus americanus*) (Looney and Eigenbrode 2012). This rapid transformation occurred before Western scientific study of the Palouse's native plants, creating significant knowledge gaps that complicate understanding previous baselines (Donovan et al. 2009).

Conservation, as a discipline focused on resource protection and management, offers a path toward restoring native grasslands like the Palouse. However, establishing conservation initiatives can be complex, as stakeholders may express environmental concerns while also weighing private property rights and legal challenges (Donovan et al. 2009). Trust plays a key role in relationships between conservation agencies, private landowners, and public land managers (Coleman et al. 2017). Wijaya et al. (2022) argue that trust is the most crucial element within an organization; if an organization does not trust a technology or application, its adoption will be swiftly rejected. Thus, in our research, it was prudent to center trust and understand its relationship to the potential use of AI in sign creation to advance conservation initiatives. Specifically, in engaging with local conservation groups and park partners, our research questions sought to understand (1) stakeholders' trust ecology related to the use of AI, and (2) if and how their participation in a facilitated process using AI influenced their trust.

METHODS

We utilized a qualitative participatory action research (PAR) approach (Kindon et al. 2010) with several organizations in eastern Washington and northern Idaho dedicated to protecting the Palouse Prairie. PAR facilitates collaboration between researchers and participants to drive deliberate and informed change (e.g., Kindon et al. 2010). In our context, PAR ensured insights came from knowledgeable and reputable informants with scientific and professional expertise, and that they helped shape the ultimate products created (interpretive signs) to advance their goals and missions. Further, given the ecologically sensitive nature of the Palouse Prairie, a PAR approach was selected over an experimental design or survey approach with a larger sample size; our primary intent was to collaboratively assist in deliberate change related to Palouse Prairie conservation education, as opposed to solely study perceptions of AI usage in this context.

We selected participants based on their prior Palouse Prairie conservation efforts or their involvement in interpretive work. Selected agencies that had previously collaborated on Palouse Prairie conservation efforts with the second author included: (1) the Palouse Land Trust, which secures voluntary conservation agreements to preserve native landscapes; (2) the White Pine Chapter of the Idaho Native Plant Society, which gathers and shares knowledge on native flora; (3) the Friends of McCroskey State Park, whose membership include family members of Virgil McCroskey, who gave land to the state of Idaho; and (4) the Idaho Department of Parks and Recreation (IDPR), the managing agency for McCroskey

State Park. Representatives from both the Coeur d'Alene Tribal Historic Preservation Office and the Palouse Prairie Foundation were also contacted multiple times but did not respond to invitations to participate, leading to their exclusion from the study. As a result, four representatives from the four participating organizations comprised the sample.

Data Collection

Following human subjects approval from the University of Idaho, pre-project (October 2024) and post-sign creation (November 2024) interviews were conducted. We interviewed one member of each group via Zoom or in person. In both interviews, a semi-structured method allowed participants to articulate (1) their focused history related to Palouse Prairie conservation; (2) their perceptions, insights, and experiences related to the use of AI, in general, and within conservation education; and (3) their reflections in relation to the research objectives and outcomes. The semi-structured format enabled investigators to ask clarifying or follow-up questions.

Following the pre-interview, participants were asked to provide scientifically accurate content related to the Palouse Prairie or McCroskey State Park. These sources (*n*=38) included published peer-reviewed articles, species lists, and required species management protocols. Sources were uploaded to Notebook LM (Google, n.d.) and were used by that AI tool, adapting prompting recommendations from Bsharat et al. (2023; see "AI Process" below). Trials were conducted using ChatGPT and Bard to explore the applicability of different LLMs, but ultimately Notebook LM was identified to be the most effective for this research. Participant insights and requests also formed the basis of the first author's AI prompts for Notebook LM. Following the creation of AI signage, the post-interview provided participants with the opportunity to review and appraise signage, suggest edits, and approve of final content. Both pre- and post-sign creation interviews conducted by the first author were recorded with participant consent, and transcribed into Microsoft Word documents for subsequent analysis.

AI Process

We used Retrieval Augmented Generation, wherein Notebook LM only utilized sources provided by the study participants to generate content. This differs from sourcing content from Notebook LM's training data or content on the internet, though the latter has since become an option. Specific steps included:

(1) Document Collected and OCR Conversion

Participants shared relevant historical and ecological documents, species lists, maps, and other content (*n*=38) mentioned by interviewees (*n*=4). Participants often shared content through physical, hard copy formats or outdated digital forms, which required conversion into machine-readable text through Optical Character Recognition (OCR) tools (i.e., Google Docs).

(2) Uploaded Content to Chatbot System

The lead author then uploaded documents to Notebook LM. At the time of this study, a notable advantage of Notebook LM compared to other tools was its ability to produce cited sources, allowing participants in the post-interviews to see precisely where the content was generated from, rather than relying on broad assumptions about the information's origin.

(3) Generated Interpretive Text Using AI

Prompts were then inserted to create interpretive signage text. Crafting clear and specific prompts is essential for generating accurate and useful outputs (Bsharat et al. 2023). One important consideration was the context window, or the amount of content a large language model (LLM) would process at once. For example, at the time of the study, OpenAI's models context window was approximately 4,000 tokens, which equates to about 3,000 words of text (OpenAI, 42, n.d.). Staying within this allotted window ensured content was fully processed and understood, preventing the LLM from omitting any critical information. Figure 1 details generic prompting language that was adjusted based on participants' topical suggestions for specific signs and locations throughout the park.

(4) Reviewed and Refined Output

AI-generated text was treated by the research team as a draft, not a finished product. The first and second authors checked for (1) factual accuracy, (2) consistency with the park's mission, and (3) clarity of messaging. Additionally, analysis included checking for appropriate tone and any interactive elements requested by interviewees (e.g., reflection questions or calls to action). Sample output with added visualizations can be seen in Figure 2.

ANALYSIS

Following both the pre- and post-interviews that bracketed the AI sign generation, we analyzed interview transcripts to understand participants' trust in AI for conservation education, and if and how their trust changed. First, a deductive coding approach (Saldana 2013) was applied using the four trust ecology types noted earlier: *dispositional, rational, affinitive*, and *procedural trust*. These trust types were frequency coded to understand the salience of each in both pre- and post-interviews. Deductive coding, or *a priori* coding, involves applying predefined theoretical concepts to categorize data. Instances of each code were identified and documented with corresponding quotes. Some quotes exhibited characteristics of multiple trust types and were

Task: *Assist in [producing interpretive signage content] on [topic/theme] at [location]. Your goal is to generate concise, professional, and engaging text suitable for wayside signs, ensuring the information is clear, accessible, and impactful for park visitors, hikers, and families.*

Tone: *Informative and engaging—captivating yet easy to understand.*

Length Constraint: *Condense key information into a few paragraphs (ideally under [150] words each) to fit interpretive signage formatting. Avoid unnecessary details or technical jargon that may confuse a general audience.*

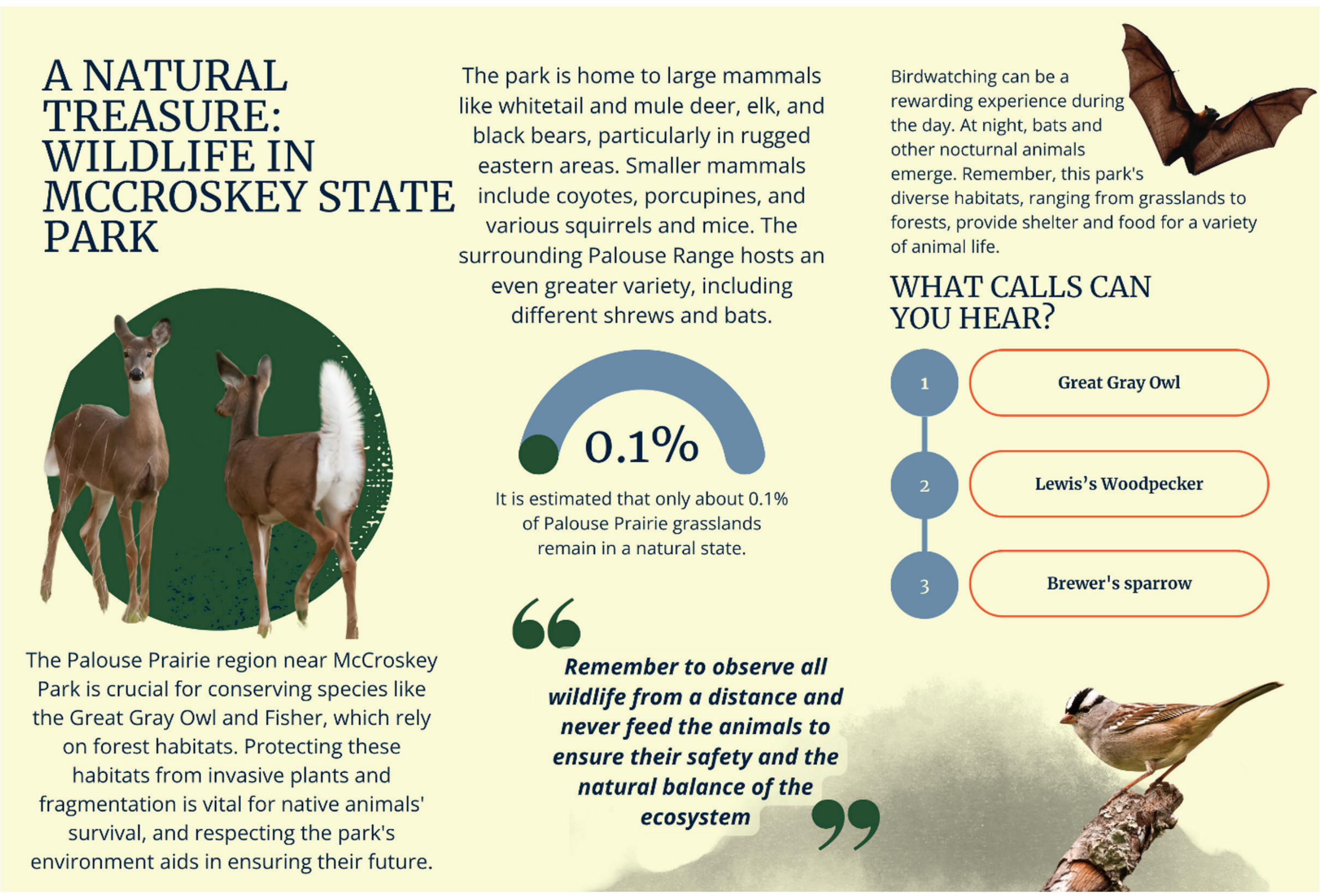
Content Focus: *Present only the most relevant facts, avoiding redundancy. Ensure key themes, significance, and interpretive messages are effectively conveyed.*

Phrasing: *Craft the output in a way that is ready for direct use on signage, requiring minimal editing.*

Further Instructions: *Using the provided source material [Notebook LM summary or additional context], distill the core message into engaging, audience-friendly text. Prioritize clarity, storytelling elements, and connection to place to enhance visitor understanding and engagement.*

▲ **FIGURE 1.** Generic AI prompting language modified for specific signage needs identified by participants.

▼ **FIGURE 2.** Sample AI-generated signage created using participants' sources.



therefore categorized under multiple codes (e.g., under both *rational trust* and *procedural trust*). Next, to compare pre- and post-AI use perceptions of trust, sentiment analysis categorized increase or decreases in mentions of trust. A second round of coding utilized six elaborative codes (i.e., *tool, oversight, convenient, reductionism, intimidation/confidence,* and *transparency*) abductively developed to further analyze trust types, linking findings to the established trust ecology types. Elaborative coding connects new data and information to an existing body of research (Auerbach and Silverstein 2003). Thus, a "top-down" approach enabled us to first leverage trust ecology and then enhance and expand established concepts to understand trust in the context of using AI to develop conservation education.

Results

All four trust types were present in both pre-and post-interviews, though their prevalence varied. Throughout both pre and post-interviews, *rational trust* was the most frequently evoked (*n*=40), followed by *procedural trust* (*n*=23) and *affinitive trust* (*n*=21), and, finally, *dispositional trust* (*n*=16). For representation (Figure 3), trust is assigned a positive value (blue), while lack of trust and distrust are categorized as a negative value (red).

A decrease in mentions of lack of trust between pre- and post-AI signage creation is immediately evident. For example, in post-interviews, *rational trust* remained the most frequently evoked trust type (*n*=20), with a notable increase in positive mentions (+7) and a reduction in lack of trust to solely one mention. One pre-interview quote evoking a lack of *rational trust* highlights the participant's lack of experience with AI: "I've gotten a little bit distrustful. And that's probably, again, just partly my ignorance and not having much experience with it or not being fully aware … of how I'm already interacting with it in benign ways." In the post-interview, the same participant stated:

> You know, I think at this point, I'm confident in … that process, the new process. Because the old process [open source] was fraught with potential, you know, problems, pitfalls, challenges, biases. And, in some ways, this kind of sounds like, from what I understand, that it comes from a little more of a neutral place to begin with. So, you're able to pull in data that's less, you know, skewed or biased. And I like that aspect. So, I would say I have, you know, probably even more confidence, which surprises me.

Thus, the same participant placed increased *rational trust* in AI after understanding the process behind its specific application and reviewing specific outputs that incorporated participants' selected sources.

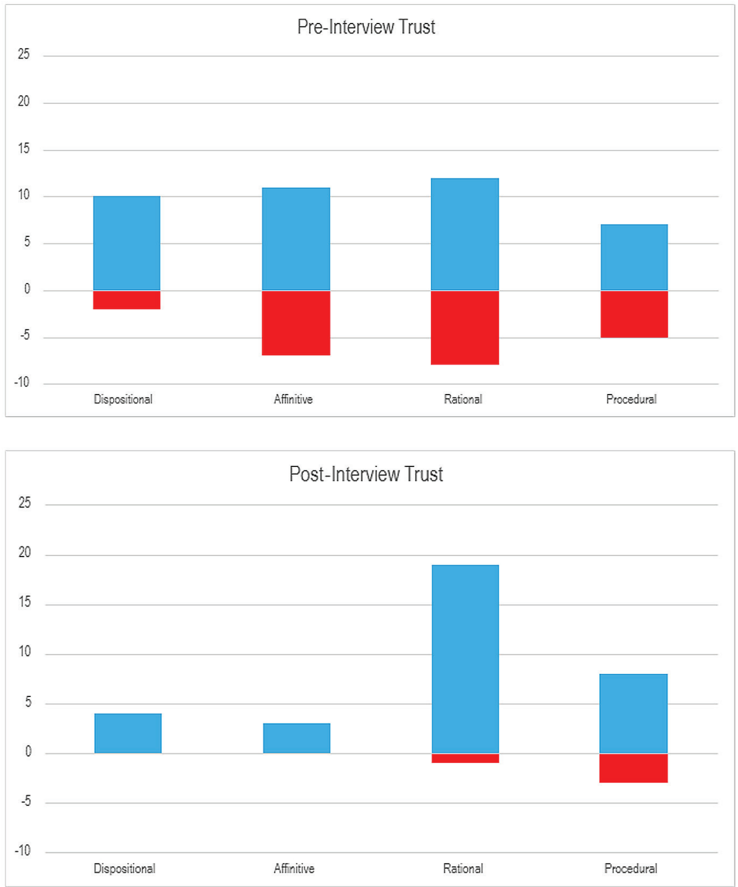


FIGURE 3. Pre- and post-interview coding of trust in AI use in conservation education by category. Statements expressing trust in this application of generative AI are highlighted in blue, while statements indicating lack of trust toward AI use are highlighted in red.

In addition to deductive coding, abductive analyses illuminated factors related to the change in trust ecology. In Table 1, each elaborative code is categorized by its relevant trust type and represented with illustrative quotes from both pre- and post-interviews. Participants mentioned the use of AI as a *tool*, stressing that it should serve as a complement to human effort. This perspective was tied to *rational trust*, as participants reflected on how AI could be leveraged in their daily work processes. When comparing elaborative codes to sentiment analysis distributions (+/–) across pre- and post-interviews, it was clear that concern for *oversight*, *reductionism*, and *transparency* contributed to the continued lack of *procedural trust* that persisted through the post-interviews. In other words, after participating in the research, participants experienced a change in *rational trust* for the potential application of AI for informal conservation education, while still perceiving that the process related to its creation was still rife with potential issues. Conversely, the *intimidation* that drove much of the lack of *affinitive trust* in the pre-interview coding (7

TABLE 1. Elaborative codes and corresponding sources of trust in AI.

Code (*Trust Type*)	*Definition*	*Pre-Use*	*Post-Use*
Tool (*Rational*)	Generative AI should not be relied upon entirely but rather used as a tool to enhance efficiency and improve the quality of work.	"It's a tool just like anything else. It's like, I guess, going to any professional: it's just one more tool that we have to go to a book or a resource or anything."	"For the most part I do think it's a great resource to use [...] I think it works pretty well."
Oversight (*Procedural*)	Establishing clear oversight for generative AI use safeguards ethical considerations and ensures responsible application.	"I just think some kind of protocol for fact checking and making sure that the credentials of who is using it, I think, is really important. Like what you have right here, like what you asked it to do, because then you could know the outcome."	"It depends on who is overseeing it, or if anyone's overseeing it, or getting the glitches out, or readjusting it. If it's not working too well. If there is no overseeing, then I don't know."
Convenient (*Rational*)	Generative AI provides user benefits by increasing efficiency, reducing costs, and improving feasibility.	"And, I mean, to be able to have this tool to help augment time and funding and all that kind of stuff. It's yeah, it's huge."	"It'd be a lot easier to do it that way, probably, than go through a designer ... all that gets more and more expensive."
Reductionism (*Procedural and Rational*)	Over-reliance on generative AI may limit diverse perspectives, as it generates content solely based on provided inputs, potentially restricting innovation and new ideas.	"I think we start relying on one tool, one book, one opinion, one piece. We just kind of it just becomes myopic and how we make decisions based on something that's growing and changing constantly. And we do the resource a disservice by using one piece and over relying on one."	"This is supposed to help you figure what to include in the sign... that's right. And maybe it can help give you ideas about what kind of art you should include. But it's not supposed to be providing that for you."
Intimidation/Confidence (*Affinitive*)	AI can be intimidating when its full scope is not entirely understood, leading to uncertainty in its application.	"I'm an older person... It's sort of intimidating. I understand the gist of it, but I think I probably initially have had a more negative reaction to it, but I understand that there are applications like this that could be very beneficial."	"I would say, I have you know, probably even more confidence. Which surprises me."
Transparency (*Procedural*)	A deeper understanding of AI promotes more effective and informed utilization.	"I think getting in front of the training and just familiarity with it. Old people like me will actually be okay with looking at it and not taking anything personally and feeling stupid again."	"It makes sense that you're using information that we gave you, which was limited ... but [I'm] not certain what you got from other agencies. But if you're using that information, it should be relevant."

mentions), dissipated as interviewees gained confidence with their knowledge of this application of AI. Ultimately, no mentions of *intimidation* or emotionally laden concern were present in the post-interviews.

DISCUSSION

We explored the use of AI to assist with interpretive content creation, while simultaneously examining the trust (or lack thereof) that conservation-oriented agency representatives held toward its application. With the endangered Palouse Prairie as context, we were curious if a PAR approach using AI to generate messaging would yield higher levels of trust in its use for partnering groups who hold conservation as central to their mission. Following this process, we noted an overall reduction in lack of *affinitive trust* and a similar reduction in the lack of *rational trust*. This shift suggests that participants placed greater trust in the predictability of desired outcomes and the process that achieved them over emotional responses related to what types of AI hallucinations might occur. Further, elaborative coding bolstered our understanding of what factors are related to these changes in trust ecology before and after the use of AI to create conservation messaging. Together, both deductive and abductive coding processes yielded multiple insights regarding what contributed to trust, distrust, or lack of trust in AI for conservation education.

First, participants frequently attributed their initial lack of *affinitive trust* to age. For example, one participant acknowledged in the pre-interview, "But again probably my age—I'm retired now, a little over a year—and you wouldn't believe how quickly technology you used in your work environment starts evaporating from your brain." This recurring theme of age-related *lack of confidence* suggests that *transparency* and guidance throughout AI processes could help mitigate such concerns. Shandilya et al. (2022) conducted an in-depth study on older adults' perceptions of AI, finding that while they were generally enthusiastic about using the technology—enthusiasm that may explain the high levels of *affinitive trust* present in the pre-interview—they also expressed concerns about its potential intrusiveness and complexity. Stypinska (2022) argues older populations are overlooked in this current technological age, referring to it as "AI ageism." They suggest that increasing communication around AI and making these deep learning technologies more accessible to a wider society could help address this gap.

In addition to the potential of age to influence initial perception, the transition from *affinitive* to *rational trust* between pre- and post-interviews also indicates the potential benefits of the facilitated PAR process. We suggest three key factors at play. First, participants mentioned that the PAR process reduced uncertainty and enhanced their own AI literacy, which Schiavo et al. (2024) and others (e.g., Jacovi et al. 2024) indicate reduces anxiety and increases positive attitudes towards AI. Second, while not explicitly mentioned by participants, the *oversight* of the lead author may have both enhanced *procedural trust* in AI, as well as demonstrated the potential for creative work that human-AI collaboration promised (see Vaccaro et al. 2024). Third, the use of Notebook LM and Retrieval Augmented Generation provided the ability to see where sources participants shared were cited, boosting potential *confidence* in content not being generated from outside of the pre-approved 38 sources. This final emphasis on *procedural trust* through *transparency* is a key component of "trustworthy AI" according to the European Union Commission's High Level Expert Group on AI (European Commission 2019), who identify transparency as the most highlighted attribute in recent ethical guideline studies.

Implications for AI-Driven Interpretation

Participants familiar with budget constraints in the natural resource field acknowledged AI's potential for interpretive signage, recognizing its ability to offset certain costs in an area where conservation efforts remain chronically underfunded (White et al. 2022). With resource constraints projected to continue for the foreseeable future, particularly in US federal agencies (stemming from Executive Order No. 14210, 2025), this is prudent. At the same time, participants strongly emphasized the ethical application of AI, consistently framing it as a *tool* rather than a replacement for human input. As one participant explained, "Using it as a tool, as a launching point, is much more realistic than just saying, 'All right, cool, did my job.'" This perspective underscores the importance, again, of *transparency* in AI applications, emphasizing its role as a supportive resource rather than an autonomous decision-maker. Walmsley (2020) discusses the concept of *functional transparency*, noting that while it is essential for building trust, achieving it can be challenging due to the complex inner workings of LLMs. The author advocates for designing AI processes with practical policies that enable users to challenge and correct computer-generated outputs. The facilitated process with conservation stakeholders we've described here is one model that does just that and serves as a potentially replicable foundation for similar efforts.

Limitations

While this study contributes valuable insights into applying AI to conservation education, several limitations should be acknowledged. First, the sample size was small (n=4); however, Boddy (2016) suggests that this is sufficient and even productive when interrogating existing theoretical frameworks with analyses such as elaborative coding. Second, coding was conducted solely by the lead author. To encourage reflexivity during analysis (e.g., Dodgson 2019), the lead author conducted multiple rounds of coding, created analytic memos to assess assumptions, and sought input from the second author and other colleagues to incorporate external perspectives. Next, the frequency coding of total mentions versus presence/absence at the interview level, potentially inflates specific quantitative representations of trust types. However, as O'Kane et al. (2021) argue, frequency coding can provide increased transparency and trustworthiness, particularly when paired with inductive or abductive coding processes to leverage the strengths of each. Finally, the landscape of AI is constantly changing and evolving. New LLMs and other tools will likely supplant those mentioned in this study, perhaps even before it goes to print; though NotebookLM is expected to receive ongoing support for the foreseeable future as part of the Google ecosystem. In any case, the importance of engendering trust in the use of AI, particularly for conservation purposes in parks and protected areas, will no doubt be a constant.

CONCLUSION

This research highlights the practical application of generative AI in creating interpretive content for budget-constrained conservation organizations and educational purposes. Findings indicate that those participating in this research effort valued the convenience of AI tools, provided their use remains *transparent* and guided by clear *procedures* that augment, instead of supplanting, human insight. We hope the method evidenced in this manuscript can support fragile ecosystems, such as the Palouse Prairie, by enabling the rapid and cost-effective development of educational signage and other materials to promote conservation and responsible visitor behavior.

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