Introduction

Science communication is the vital bridge between knowledge production, information trust, and the public (Weingart & Guenther, 2016). It has often been recognized as the third mission of many universities, particularly land grant universities, alongside research and teaching (National Academies of Sciences, Engineering, and Medicine [NASEM], 2017). It serves as a crucial mechanism for translating complex scientific information into accessible, meaningful and understandable narratives, fostering public engagement, and promoting informed decision-making (Parella et al., 2023). Burns et al. (2003) defined science communication as "the use of appropriate skills, media, activities, and dialogue to produce one or more of the following personal responses to science: Awareness, Enjoyment, Interest, Opinions, [and] Understanding" (p. 191). This definition highlights the multifaceted nature of science communication, which extends beyond mere dissemination of facts to actively shaping how people perceive, interact with, and apply scientific knowledge in their daily lives.

Science communication is often conceptualized as a dynamic exchange between experts, such as scientists, research institutes, laboratories, and universities, and various public audiences (Schafer & Fahnrich, 2020). It encompasses a broad range of activities, including public engagement by individual scientists, strategic communication by scientific organizations (e.g., public relations or marketing efforts), science journalism, and informal science education (NASEM, 2017). Within this diverse landscape, professionals adopt different approaches depending on their objectives, whether it be enhancing public understanding of science or fostering meaningful dialogue between scientists and society (Schäfer, 2023).

Effective science communication is essential for addressing societal challenges, bridging gaps between science and policy, and cultivating trust between experts and the public (NASEM, 2017). Science communication has played a crucial role in agricultural extension and communication for the past two centuries and remains essential today (Parella et al., 2023). It focuses on disseminating scientific research that addresses real-world challenges and provides educational insights. Historically, the primary goal of science communication was to inform the public about significant and applicable scientific discoveries (Weingart & Guenther, 2016). To achieve this goal, extension educators have traditionally relied on various communication technologies to reach their target audiences (Donnellan & Montgomery, 2005). Conventional methods, such as newsletters, magazines, fact sheets, and pamphlets, were widely used to disseminate information (Rumble et al., 2022). However, the advent of digital media has transformed science communication; introducing new tools and expanding its reach (O'Brien et al., 2024). Online platforms have not only enhanced scientific information accessibility but have also contributed to the rise of the 24/7 news cycle and the emergence of "citizen journalists," fundamentally altering the landscape of agricultural communication (Irani & Doerfert, 2013; Parella et al., 2023).

One of the emerging technologies with significant implications for science communication is generative artificial intelligence (AI). Machines can now exhibit cognitive abilities such as intelligence, language processing, knowledge representation, and reasoning, capabilities once considered exclusive to the human mind (Lim & Schmälzle, 2024). AI, broadly defined as computer systems capable of making intelligent decisions or emulating human cognition, is a rapidly evolving field that is reshaping daily life (Shank et al., 2023). AI technologies such as ChatGPT, along with similar systems like Google's Bard/Gemini and Meta's Llama, are powered by large language models (LLMs; Lim & Schmälzle, 2023). These LLMs utilize transformer-based neural networks trained on vast amounts of text data, enabling them not only to process and categorize language but also to generate text that closely resembles natural human communication (Bubeck et al., 2023). Moreover, due to their extensive training data, LLMs can produce content on virtually any topic (Lermann Henestrosa & Kimmerle, 2024). As a result, written language is no longer an exclusively human domain (Bubeck et al., 2023).

Generative AI, such as ChatGPT, is revolutionizing science communication by providing easily accessible information on a wide range of scientific topics (Kessler et al., 2025). LLMs have greatly advanced AI's ability to generate content, improving both the speed and quality of production (Alvarez et al., 2024). Additionally, they have enhanced the persuasiveness of AI-generated content (Huang & Wang, 2023). This shift marks the emergence of AI-Mediated Communication, where technology not only facilitates but also enhances, refines, and even generates interpersonal exchanges (Jakesch et al., 2019).

AI presents new opportunities for accessing knowledge and enhancing science communication. As Lermann et al. (2024) suggests, AI can make scientific information more understandable and accessible by tailoring content to specific audiences, summarizing research, clarifying key points, and simplifying complex concepts. Thus, AI may play a crucial role in improving public understanding of scientific concepts by addressing misconceptions and misinformation with accurate information from credible sources (Kessler et al., 2025). It may also foster trust in science (Beckmann et al., 2025) and promote dialogue between scientists and the public by offering interactive platforms for engagement such as the use of AI avatars (Baake et al., 2025).

AI has the potential to generate high-quality, creative, and informative content, creating new opportunities for researchers and practitioners to enhance their science communication efforts using LLMs (Baake et al., 2025; Kessler et al., 2025). Carufel (2020) emphasized that the use of AI in consumer messaging is essential for the success of public relations professionals. These capabilities have already demonstrated effectiveness in various fields, particularly in health communication. For example, studies have shown that messages generated by LLMs are clear, informative, and well-argued, making them valuable tools for conveying complex health information to the public (Karinshak et al., 2023; Lim & Schmalzle, 2023).

While AI-generated content offers exciting opportunities for creative expression, personalized user experiences, and enhanced communication (Cassell, 2019; Jin et al., 2020), it also presents significant ethical and societal challenges. Research has shown AI leaves out important details (Birhane et al., 2023), provide plausible sounding but false or misleading information (Binz et al., 2025), and may even limit the scope of research conclusions by oversimplifying text (Peters & Chin-Yee, 2025). For example, deepfakes pose serious risks to trust, privacy, and information integrity on social media, as they can be used to manipulate public opinion, spread disinformation, and impersonate individuals (Güera & Delp, 2018; Chesney & Citron, 2019). Due to these concerns, scientists and politicians have raised alarms about generative AI, with many leading researchers signing a declaration calling for it to be treated as a societal threat on par with nuclear conflict and pandemics (Huschens et al., 2023). This underscores the importance of transparency and credibility to ensure AI-generated information is used responsibly and does not harm users or society (Labajová, 2023).

Public expectations of emerging technologies play a crucial role in shaping how scientific innovations are understood and perceived (Scheufele & Lewenstein, 2005). The benefits of AI largely depend on public acceptance and adoption, which are not guaranteed. If people remain hesitant to trust AI, its potential positive impact on society by conveying complex material to the public may be significantly limited (Castelo & Ward, 2021). If key users do not recognize or accept the output from LLMs as accurate, it may be disregarded, regardless of its objective correctness.

Understanding how people receive and perceive LLM outputs, shaped by various social and psychological factors, is an important yet under-explored area (Harasta et al., 2024). It is widely recognized that examining attitudes toward new technologies is essential for understanding public support or opposition to them (Wu et al., 2020). By analyzing how individuals respond to AI, researchers can examine how AI is framed as a viable and effective solution to various challenges. This framing not only influences public opinion but also has the potential to shape the future development and adoption of AI (Brennen et al., 2022).

Due to the relative novelty of AI, the role of AI as a source of communicative content with the public remains largely underexplored (Lim & Schmälzle, 2024), especially as it relates to sharing agricultural content. Agricultural scientists have discussed the barriers to incorporating AI within precision agriculture practices to improve crop production (Gardezi et al., 2024), recognizing the importance of establishing farmer trust in the technology through "[m]odel transparency and explainability" (p. 1219). Additionally, researchers have discussed the benefits of utilizing AI within the realm of agricultural extension to help extension professionals efficiently reach producers with valuable, current information relevant to their farms while recognizing the AI limitations of farmer acceptance, technology adoption cost, and the lack of a human touch (Jayasingh et al., 2024). However, to our knowledge, no prior research has specifically examined consumer perceptions of AI-generated content within the context of agricultural extension and communication. Investigating how audiences respond to AI-generated messages in agricultural communication is essential for understanding its potential benefits and limitations.

The nuances of communication perceptions must be considered when sharing science about contentious agricultural issues such as genetically modified (GM) food, animal welfare, or climate change (Beall et al., 2017; Lamm et al., 2025; Lang, 2013; McKendree et al., 2014). When communicating with the public, scientists who share information on contentious topics may be viewed as more credible or less credible and their personal motivations questioned depending upon the stance they take in communication, whether sharing information only, information in a non-controversial manner, or in a controversial manner (Beall et al., 2017). Additionally, the topic of public contention ultimately plays a role in audience perceptions surrounding a scientist's credibility (Beall et al., 2017). For example, Lang (2013) found university scientists were the source U.S. audiences trusted most to make sound decisions about GM food production, followed by farmers, then environmental groups. However, Brewer and Ley (2013) found that while university scientists were highly ranked as sources of information about the environment, scientific television shows were the most trusted environmental information source. More recently, Macready et al. (2020) found farmers more trustworthy than governmental authorities or food manufacturers when studying residents of five countries in Europe. Lamm et al. (2025) found there may be different dimensions of trust impacting public perception of science communication messages arguing previous research examining trust in science is limiting.

Specific to animal agriculture, scientific messaging around how we raise and treat animals is critical for consumer trust in their food supply (Belk et al., 2025). The contentious topic of animal welfare is at the forefront of many conversations in Western society, with audiences reportedly eating less meat because of animal welfare concerns (Fonseca & Sanchez-

Sabete, 2022; McKendree et al., 2014). When a survey explored U.S. audiences' sources of animal welfare information, findings revealed over half of the respondents did not have a source, while those who did gained most of their information on animal welfare from animal protection activist organizations, and only 1% used university scientists (McKendree et al., 2014). Therefore, it is necessary to examine topics that are considered controversial and non-controversial to gain a more holistic view of credibility as it relates to AI in the context of agricultural science.

The purpose of this study was to determine if consumers' perceived transparency and source credibility of social media posts sharing agricultural scientific information differed based on posts generated by AI versus those written by a scientist (human). The study responds to recent advancements in LLMs and seeks to provide essential insights for the responsible design, development, and adoption of LLM-powered applications that automate content creation in fields such as food and nutrition.

Literature Review

Perceptions of Artificial Intelligence

With easy access to LLM-powered applications such as ChatGPT, Bard, and Copilot, many people are eager to explore and adopt this groundbreaking technology. However, the widespread adoption of LLMs faces challenges that go beyond achieving high accuracy in tasks, even when that accuracy approaches human levels. Notably, people often rate AI-generated content less favorably than human-created content. Improper adaptation to emerging technologies, coupled with a lack of trust and feelings of anxiety, can prevent individuals from making rational decisions when interacting with these important innovations (Bochniarz et al., 2022; Broadbent, 2017; Suen & Hung, 2023).

Historical records indicate people are frequently skeptical when new technologies are introduced, particularly AI and computer algorithms (von Eschenbach, 2021). Perceptions of AI are often predominantly negative (Ragot et al., 2020), and some individuals experience mild to moderate aversion (Castelo & Ward, 2021). Scholars have argued increasing reliance on AI could lead to 'algocracy', a scenario where algorithm-based systems limit human involvement in and understanding of public decision-making (Danaher, 2016, p. 246). This is especially relevant for AI, as it is often opaque, with its internal mechanisms hidden. While observers can see inputs and outputs, the process through which AI arrives at conclusions is not transparent, raising questions about trust in these systems. The public has increasingly demanded greater transparency in science communication, seeking complex information presented in a more digestible manner (Lasser et al., 2020). To avoid negative consequences and build accountable systems, many suggest "opening the black box" of AI decision-making and increasing transparency and trustworthiness (de Fine Licht & de Fine Licht, 2020). Previous research in the use of AI in journalism found respondents with higher levels of knowledge about automated journalism employing the use of AI had equal or stronger preferences for articles attributed to automated journalism, while those with lower levels of knowledge about the subject had stronger preferences for news stories with human attribution (Jang et al., 2022). Given this, it may be possible to instill trust in AI sources as public audiences increase in their knowledge of AI models and how they generate information.

The published literature suggests people may be less likely to trust AI as much as they would trust a human in various domains (Castelo & Ward, 2021). In many fields, people evaluate

AI differently from humans, even in identical situations (Shank et al., 2023). As one example of several that will be shared, both music professionals and the public have shown hesitation toward music generated by AI (Shank et al., 2023). Jakesch et al. (2019) found that: (1) when presented with entirely AI-generated profiles, people trust them as much as human-written profiles, but (2) when presented with a mix of AI- and human-written profiles, they tend to mistrust those they believe to be AI-generated. Some people also believe that AI is less capable of handling subjective tasks, such as giving dating advice, making them less likely to accept AI recommendations (Castelo et al., 2019). In a study of AI recommendations on shopping websites, people preferred AI recommenders for selecting products based on utilitarian attributes, like warmth in winter coats, but favored human recommenders for aesthetic choices, such as coat appearance (Longoni & Cian, 2020). Additionally, when people know AI was involved in content creation, they tend to rate the content less favorably or prefer content created without AI involvement (e.g., email writing, Liu et al., 2022; generated paintings, Ragot et al., 2020; Airbnb profile writing, Jakesch et al., 2019; translation of written content, Asscher & Glikson, 2023). In health-related contexts, people generally prefer consulting human practitioners over AI-based technologies like chatbots (Miles et al., 2021). This preference stems from the belief that AI lacks personalization and competence in addressing individual needs (Longoni et al., 2019). Improper adaptation to emerging technologies, combined with a lack of trust and anxiety, can hinder people from making rational decisions when interacting with these innovations (Bochniarz et al., 2022; Broadbent, 2017; Suen & Hung, 2023). In summary, past research suggests that people generally view both AI's actions and products more negatively than those of humans (Shank et al., 2023).

Perceived Transparency

Transparency involves deliberately making relevant information, both positive and negative, available to the public (Rawlins, 2008). Van der Cruijsen and Eijffinger (2010) found that insufficient transparency perceptions can negatively affect people’s actions, perceptions, expectations, and trust in organizations. Their study also showed that higher transparency perceptions are associated with greater trust. Even when science is inherently transparent, consumer skepticism can only be overcome if individuals perceive the information as transparent (Goodwin, 2013). In other words, if the public is unaware of or unable to access information, they are unlikely to trust it (Grimmelikhuijsen, 2009). Thus, examining consumers’ perceived transparency of scientific information is essential for effective global science communication. Scholars increasingly recognize that trust related to transparency depends on both consumer access and perception, as well as the organization’s efforts to be transparent (Goodwin, 2013; Song & Lee, 2016). Kang and Hustvedt (2014) used perceived transparency to predict consumer trust in a company, finding that consumers’ perceptions of a company’s transparency in areas such as production practices, labor conditions, and community responsibility influence their trust, attitudes, and purchasing intentions. Research also shows that perceived transparency significantly increases consumers’ online purchasing intentions (Zhou et al., 2018).

Source Credibility

The impact of source effects has been widely studied in persuasion and communication research (Boster & Carpenter, 2021). Extensive literature examines how different source characteristics, including credibility and trustworthiness influence individuals’ attitudes and behaviors (O'Keefe, 2015). Recent research suggests that digital public relations strategies should consider how source credibility affects message effectiveness (Lim & Brown-Devlin, 2021). Indeed, grasping human-centered approaches to evaluating the credibility of AI-generated information is crucial for effectively navigating the complex information landscapes of the AI age (Ou et al., 2024). Credibility is generally defined as "a perceptual state, meaning the result of an attribution process in which message recipients form judgments about the sources and evaluate them as either credible or not" (Jackob, 2008). As a result, people frequently rely on the trustworthiness or perceived credibility of a messenger as a shortcut in forming opinions or deciding whether to accept a message (Brewer & Ley, 2013). The study of credibility has a long history, with its origins dating back to the 1950s (Huschens et al., 2023) and typically comprise three distinct levels: source credibility, media credibility, and message credibility (Appelman & Sundar, 2016). In other words, when assessing whether information is trustworthy or credible, we consider three factors: 1) who is the sender of the information (source credibility), 2) through which channel the information is conveyed (media credibility), and 3) how the message is presented (message credibility) (Hellmueller & Trilling, 2012).

In science communication, ensuring the credibility of both the medium and the message is crucial, potentially even more so than in other areas of social life. Across different times and countries, professions like medical doctors, teachers, judges, and scientists consistently rank highest in trustworthiness because they are perceived as serving the common good (Wu et al., 2020). In general, science communication from governments, public relations offices at universities and science organizations, and other interested parties is often perceived as less credible than communication from academic scientists and science journalists (Weingart & Guenther, 2016). Within agricultural contexts, university scientists have historically ranked among the most trusted agricultural information sources on divisive topics such as genetically modified foods and environmental conservation (Brewer & Ley, 2013; Lang, 2013; Martin et al., 2016), indicating a certain degree of existing credibility with public audiences. Consequently, the credibility of science is closely tied to the effectiveness and reliability of science communication (Weingart & Guenther, 2016). Multiple studies have explored the credibility associated with using AI as journalistic authors, finding that readers perceive articles attributed with AI authorship to be less credible and intelligent than human authorship (Lermann Henestrosa & Kimmerle, 2024) and that readers who perceived that news articles were authored by AI were more likely to have negative perceptions of the articles' source and message credibility (Jia et al., 2024).

Purpose and Research Hypotheses

The purpose of the study was to determine if consumers' perceived transparency of social media posts sharing agricultural scientific information differed based on the posts being generated by AI versus a scientist (human) using both a benign (animal nutrition) topic and a more controversial (animal welfare) topic. The objectives of the study were to:

1. Describe consumers' perceived transparency of social media posts sharing agricultural scientific information with a more benign (animal nutrition) topic and a more controversial (animal welfare) topic when they were generated by AI and by a scientist before and after being told how the message was generated.
2. Determine if consumers' perceived transparency of social media posts sharing agricultural scientific information with a more benign (animal nutrition) topic and with a

more controversial (animal welfare) topic differed when they were told how the social media post was generated (AI or scientist).

The following hypotheses were tested:

H_1: Respondents will exhibit a lower level of perceived transparency after it is revealed the social media post was AI-generated.

H_2: Respondents will exhibit a higher level of perceived transparency after it is revealed the social media post was scientist-generated.

Methods

An experimental design embedded in an online survey was used to test the hypotheses. The population of interest was consumers in the U.S. aged 18 and older. Data were collected from 1,011 adult U.S. consumers aged 18 years and older using Qualtrics, an online survey platform, in June 2024. Non-probability opt-in sampling methods were used; a common method assisting public opinion researchers in making population estimates (Futri et al., 2022). Comparison studies examining differences between non-probability and probability sampling methods have indicated using non-probability sampling methods obtains responses equivalent to, or even greater than, those obtained using probability sampling methods (Baker et al., 2013). Qualtrics used their standard protocols to incentivize and compensate respondents. Using the Internet to recruit respondents does have limitations. Individuals inclined to opt in to incentivized panels and/or access to the Internet can introduce sampling bias. Quotas set *a priori* ensured the respondents were representative of U.S. consumers based on where they were geographically located, their age, reported gender, race, and ethnicity (Futri et al., 2022; Lamm & Lamm, 2019).

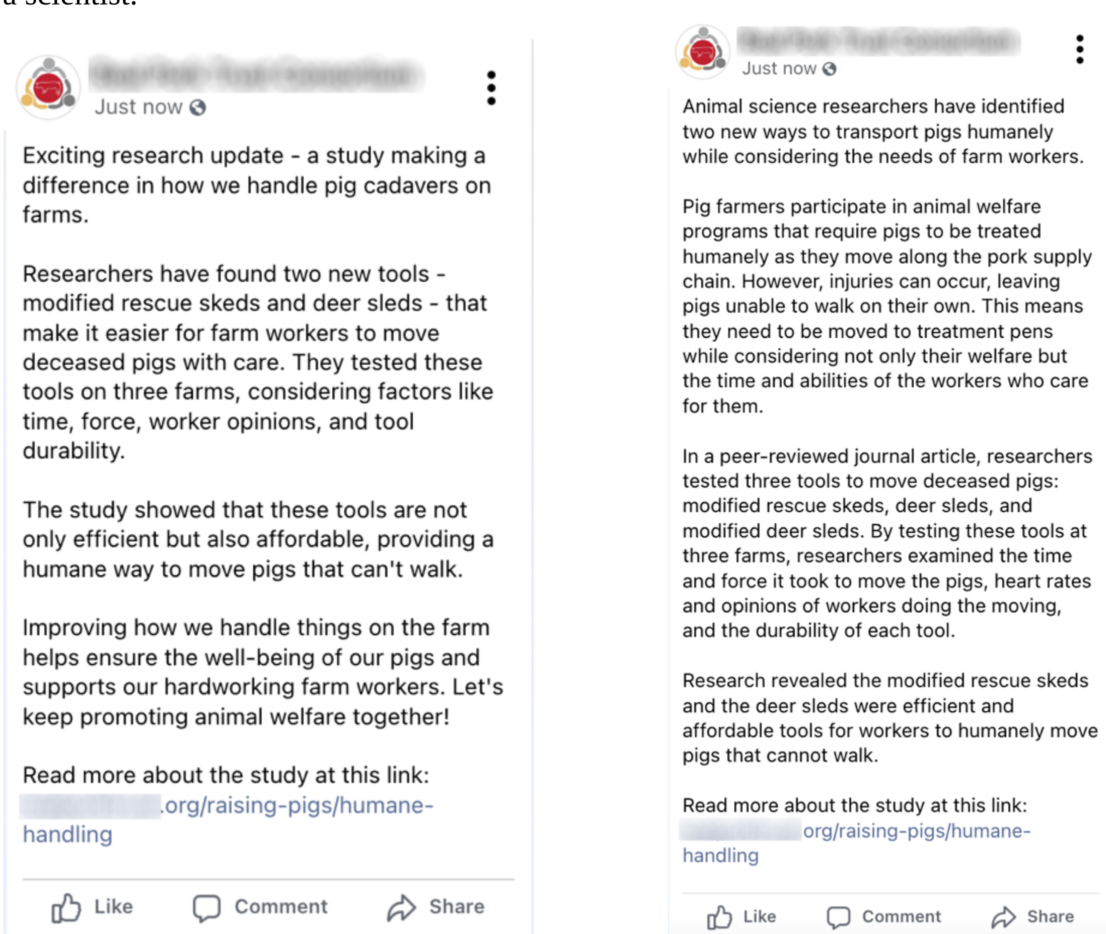
The instrument was reviewed after initial development for content and face validity by faculty members who specialize in agricultural communication, agricultural research methods, survey design, and animal science. The University of Georgia Institutional Review Board (IRB #00008098) then approved the instrument design and research protocol. Scale reliability was assessed using a pilot test of 50 respondents, representative of the population of interest. No adjustments were needed with all scales exhibiting a Cronbach's alpha coefficient above .70 (Cortina, 1993).

Upon entering the survey, the 1,011 respondents were randomly assigned to four treatment groups. Respondents received one of four social media posts:

1. Animal welfare message developed by AI (Figure 1a).
2. Animal welfare message developed by a scientist (Figure 1b).
3. Animal nutrition message developed by AI (Figure 2a).
4. Animal nutrition message developed by a scientist (Figure 2b).

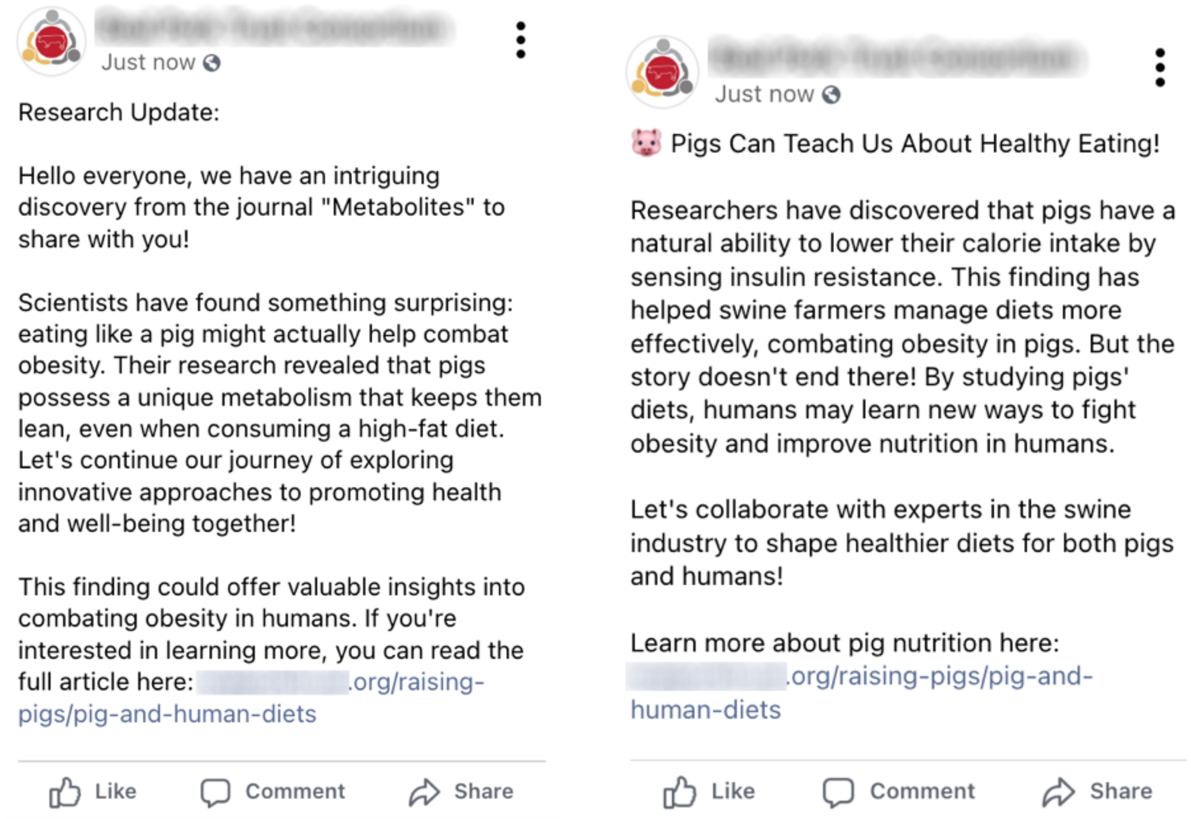
Facebook was selected as the social media platform example because it is the most broadly used social media platform in the U.S. and would most recognizable to survey respondents (Pew Research Center, 2023). The animal welfare social media posts were designed to share scientific findings from the article titled "Modified wean-to-finish mat as an alternative handling tool for moving grow-finish pig cadavers: A pilot study" published in 2019 written by an animal science professor. The animal nutrition messages were designed to share scientific findings from the peer reviewed research article titled "Eat like a pig to combat obesity" published in 2023 written by an animal science professor. The social media posts generated by AI were created using ChatGPT. Specifically, the AI social media post was generated by providing ChatGPT with an abstract of the article and requesting it to "Create a Facebook post describing the findings of the study for a public audience." The AI generated social media post was reviewed by animal science faculty members for accuracy of the content but was not altered to ensure the post exhibited the typical nature of AI-generated text. The version of the Facebook post generated by a scientist was created by a faculty member focused on agricultural science communication and reviewed by animal science faculty members for content accuracy.

Figure 1. Social media post sharing information about animal welfare developed by (a) AI and (b) a scientist.



(a) (b)

Figure 2. Social media posts sharing information about animal nutrition developed by (a) AI and (b) a scientist.



(a) (b)

Respondents were required to spend a minimum amount of time reading the social media post they received to ensure they viewed the content. The next screen button appeared after 20 seconds. Upon progressing to the next page, respondents were asked to indicate their perceived transparency of the message they read before knowing how the post was generated.

Perceived transparency of the social media post was measured by asking respondents to indicate how they felt about the message between seven sets of adjectives using a five-point semantic differential scale developed by Wu et al. (2020). Sets of adjectives included complete/incomplete, relevant/irrelevant, biased/unbiased, accurate/inaccurate, reliable/unreliable, transparent/not transparent, and correct/incorrect with a five indicating a preference for the more transparent adjective and a one indicating a preference for the less transparent adjective. Responses to the seven items were then averaged to create a perceived transparency score. The perceived transparency scale before how the social media post was generated was revealed was also found reliable ($\alpha = .86$).

After the initial response, respondents were notified of how the social media post was generated (AI or scientist). Respondents were then asked to respond to the same set of seven semantic-differential items to measure perceived transparency after how the social media post was generated was revealed. Again, the responses to the seven items were averaged to create a perceived transparency scale after how the social media post was generated was revealed. The perceived transparency scale after reveal was also found reliable ($\alpha = .90$).

The data collected were deemed an adequate sample size for data analysis with 1,011 U.S. consumers responding to the survey (Dolnicar, 2014). A full demographic description, prior to weighting, can be viewed in Table 1. Respondents' age ranged from 19 to 90 (M = 50.68, SD = 10.09). The largest group of respondents were White (74.9%), and almost half reported having at least a two-year college degree (48.6%). Total family income (before taxes) was reported to be less than $149,999 (92.6%). Over a quarter of the respondents (28.3%) had children under the age of 18 living in their home. Only 11.3% of the respondents reported having a special diet (vegetarian, pescatarian, vegan or paleo).

Table 1

Demographics of Respondents Prior to Weighting (N = 1011)

	n	%
Sex		
Male	465	46.0
Female	546	54.0
Race*		
White	757	74.9
Black	149	14.7
Asian	71	7.0
American Indian or Alaska Native	64	6.3
Other	45	4.5
Hispanic Ethnicity	190	18.8
Education		
Less than 12th grade	27	2.7
High school diploma	252	24.9
Some college	241	23.8
2-year college degree	127	12.6
4-year college degree	230	22.7
Graduate or Professional degree	134	13.3
Marital Status		
Single	333	32.9
Married	363	35.9
Living with a partner, not married	85	8.4
Divorced	148	14.6
Separated	17	1.7
Widowed	65	6.4
Family Income		
Less than $24,999	238	23.5
$25,000 - $49,999	283	28.0
$50,000 - $74,999	208	20.6
$75,000 - $149,999	207	20.5
$150,000 - $249,999	51	5.0
$250,000 or more	24	2.4

	n	%
Children under the age of 18 currently living in the home		
0	725	71.7
1	147	14.5
2	103	10.2
3 or more	36	3.6
Special Diet		
Vegetarian (no meat, chicken or fish/seafood)	54	5.4
Pescatarian (no flesh of any animal except fish/seafood)	21	2.1
Vegan (no animal or seafood products of any kind, including dairy)	18	1.8
Paleo (no dairy or grain products and no processed food)	20	2.0
Political Ideology		
Very Liberal	126	12.5
Liberal	186	18.4
Moderate	440	43.5
Conservative	160	15.8
Very Conservative	99	9.8

Note. *Respondents allowed to select more than one race therefore percentages do not equal 100%.

Data analysis was conducted in SPSS using descriptive statistics and paired samples *t*-tests. Maxwell and Delaney (2004) indicated only appropriate tests aligned with hypotheses should be run, rather than all possible post hoc comparisons, to reduce Type I error rates. In this case, only two groups were compared at a time (before and after the source was revealed within each content area and source) as indicated in our hypotheses. Significance level was established as .05 a priori. Effect size was interpreted using Cohen's (1988) *d* (small = .20, medium = .50, large = .80).

Limitations

The online nature of the survey introduced bias because only respondents with internet access were eligible to participate. However, the study aimed to understand interpretation of social media information accessed online; therefore, active online users were an appropriate target audience. Additionally, while the Facebook posts presented to respondents in each treatment contained links to learn more about the subject, the links and reaction buttons were not clickable, potentially hindering the typical user interaction experience to which respondents would be accustomed on Facebook. While Facebook was selected as the most broadly used social media platform within the United States that can utilize text alone as a posting medium, the study did not account for Facebook use among respondents. Future studies may benefit from including variables related to social media use to further explore the nuances of perceived transparency and source credibility associated with AI-generated messages.

Results

Overall, respondents in all four treatment groups reported a neutral level of perceived transparency of all four social media posts with mean scores ranging between 3.02 and 3.54 (see Table 2). Perceived transparency of both animal welfare social media posts was higher than those using animal nutrition as the subject matter before it was revealed how the posts were generated was revealed. However, the respondents who received the animal welfare social media post generated using AI reported a lower level of perceived transparency than those who received the animal nutrition social media post generated by a scientist after how the posts were generated was revealed.

Table 2

Perceived Transparency of Social Media Posts Before and After How the Post was Generated was Revealed by Treatment Group.

		Perceived Transparency			
		Before		After	
	n	*M*	*SD*	*M*	*SD*
Animal welfare - AI-generated	250	3.46	.87	3.33	.98
Animal welfare - scientist-generated	251	3.54	.78	3.72	.79
Animal nutrition - AI-generated	253	3.02	.85	2.92	.99
Animal nutrition - scientist-generated	257	3.38	.77	3.61	.80

Four paired *t*-tests were used to determine if perceived transparency changed when the respondent was told how the social media post was generated (see Table 3). Perceived transparency significantly decreased when respondents were notified the social media post was AI-generated for both the animal welfare (ΔM = -.13) and animal nutrition (ΔM = -.10) social media posts. Both had a small effect size. Therefore, the first hypothesis was supported.

Table 3

Differences in Perceived Transparency of Social Media Post Before and After Revealing Source

	ΔM	*t*	*d*	*p*
Animal welfare - AI-generated	-.13	-3.14	-.20	.00**
Animal welfare - scientist-generated	.19	4.60	.29	.00**
Animal nutrition - AI-generated	-.10	-2.28	-.14	.02*
Animal nutrition - scientist-generated	.23	6.83	.43	.00**

*$p < .05$; **$p < .01$

Conversely, perceived transparency significantly increased when respondents were notified the social media post was scientist-generated for both the animal welfare (ΔM = .19) and animal nutrition (ΔM = .23) content. Both had small effect sizes. Therefore, the second hypothesis was supported.

Discussion, Implications, and Recommendations

Science communication is a priority for universities focused on disseminating research-based information to the public (Weingart & Guenther, 2016). The rapid development of digital communications platforms has drastically altered how science communicators achieve communication goals (Irani & Doerfert, 2013). Generative AI, and its persuasive capabilities, pose a potential solution to the challenges of creating accurate, tailored science communication content in a short amount of time for public audiences (Lermann et al., 2024), especially when communicating about contentious and time-sensitive agricultural issues. However, little was known about public trust in AI generated messaging and if the use of this emerging tool could have unforeseen negative consequences.

The findings of the present study revealed that when communicating with public audiences about animal science topics, regardless of their contentious nature, scientists are more trusted to create social media science communication messages when compared to those created using generative AI. The findings aligned with previous studies, confirming the source of information significantly influenced perceived transparency but contradicted that the contentiousness of subject matter impacted perceptions of transparency (Wu et al., 2020). In this case, the source developing the message being AI was detrimental despite subject matter, whereas the source developing the message being a scientist was beneficial despite subject matter. This finding aligns with previous literature which asserts high levels of public trust in university scientists (Brewer & Ley, 2013; Lang, 2013; Martin et al., 2016) alongside public distrust in AI to tackle complex scientific topics (Lermann et al., 2024). However, societal shifts in trust in scientists may impact this finding in the future. Previous research found members of the public felt AI can be used to spread disinformation and manipulate public opinion (Chesney & Citron, 2019; Güera & Delp, 2018), which may contribute to the lack of perceived transparency in the science communication message developed using AI in the current study.

Perceived transparency was higher for both animal welfare messages than it was for both animal nutrition messages before how the posts were generated was revealed. The higher perceived transparency for the animal welfare messages could be because revealing unflattering and potentially negative information about animal welfare, such as moving pig cadavers humanely, is a glimpse into relevant information which the public may not often see in their everyday communications about animal science (Rawlins, 2008). Perhaps the respondents appreciated the open nature of this communication, causing them to have higher perceptions of the message transparency. This partially aligns with the findings of Beall et al. (2017) which suggests respondents' perceived scientist credibility can be influenced by the way they deliver information about a controversial topic. However, the animal nutrition message discussed how a discovery about pig nutrition could help inform human nutrition, which may have been more palatable. Respondents' perception of transparency may have been lower because they did not feel as if they were gaining access to exclusive or typically inaccessible information. While previous research has shown lack of access to information leads to lack of trust (Grimmelikhuijsen, 2009), future studies may benefit from determining if trust in science communication messages increases when public audiences are provided with information typically considered inaccessible or non-transparent in the animal science space.

Perceived transparency of both social media posts generated by AI significantly decreased upon revealing the posts were generated by AI and checked for accuracy before posting. This aligns with concerns around the use of AI in various fields where audience members are unwilling to trust generative AI content (Asscher & Glikson, 2023; Jakesch et al, 2019; Liu et al., 2022; Ragot et al., 2020). A preference for human-generated content over AI-generated content may be based on the belief that AI cannot consider the needs of an individual (Longoni et al., 2019). However, the posts presented in the current study were not tailored to individual needs of audiences but were created to be broadly applicable to Facebook users. This preference for information from university scientists over AI in an impersonal matter indicates a high level of trust in university scientists that should be encouraging to those who are trying to share their scientific research with the public. Future studies should examine consumer perceptions and trust of tailored AI messages relevant to consumer personal interests (e.g., fitness, food purchasing, environmental sustainability) in comparison to impersonal messages created by scientists to determine if personalized messaging from AI can influence perceived levels of trust.

The lower levels of perceived transparency for AI-generated messages imply using AI to efficiently deliver science communication messages about university research should be used cautiously. The findings of the current study suggest utilizing AI in communication may be detrimental to the credibility of universities should public audiences perceive messages are written by human sources and then discover they are generated by AI. Given this finding, it is recommended science communicators limit their use of AI in generating content until it is more widely accepted or the nuances of trust in AI for various subject matter areas is better understood.

The available time for scientists to translate and tailor their research information for public audiences is limited and the use of AI could be a valuable time saving tool. Future research is recommended to explore factors influencing public acceptance of AI technology. Previous research indicates individual knowledge of AI has been associated with a higher preference for AI-generated content (Jang et al., 2022); therefore, the findings imply the scientific community should begin explaining the process by which AI generates content to the public to generate support for a highly efficient tool that could dramatically increase the amount of scientific information being shared with public audiences should it be more readily accepted. Additionally, future studies should incorporate scales to measure consumer knowledge of AI technologies, trust levels in AI, and a diverse array of agricultural messages written by AI to determine how each factor plays into message acceptance.

The findings imply the public acceptance of AI as an efficient tool in creating science communication messages is currently limited in the U.S. Additional research should be conducted in other countries to determine if AI acceptance as a science communication tool is consistent with these findings. Additionally, science communication messages with AI used for content generation should be tested on other platforms (e.g. Instagram catering to younger audiences or Weibo used in China) to gain further insights into its acceptance with diverse audiences, especially younger generations who may be utilizing AI to complete tasks in their everyday lives. As AI becomes a more prevalent tool and topic of debate in the global society, it is the responsibility of science communicators to continue to explore its responsible uses and contributions to the field.

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