Title: **Silencing controversial realities through prompt revision: The erasure of intensive livestock farming in text-to-image generative AI**

Authors: Kehan Sheng[1], Frank A.M. Tuyttens [2, 3], Marina A.G. von Keyserlingk[1]*

Affiliations:

[1]Animal Welfare Program, The University of British Columbia; Vancouver, V6T 1Z6, Canada

*Corresponding author. Email: marina.vonkeyserlingk@ubc.ca; Phone number: +1 604-306-5721

[2]Animal Sciences Unit, Flanders Research Institute for Agriculture, Fisheries and Food (ILVO); Melle-Merelbeke, 9090, Belgium

[3]Department of Veterinary and Biosciences, Faculty of Veterinary Medicine, Ghent University; Melle-Merelbeke, 9090, Belgium

Abstract

Generative AI like ChatGPT is increasingly integrated into people's daily lives as a vehicle for information access and to aid decision-making. However, misinformation and biases are embedded in these models which raises ethical concerns. Previous research has revealed AI biases regarding human attributes like skin tone, gender, and geo-culture. To mitigate these biases in text-to-image generative AI models, companies like OpenAI introduced prompt revision, an implicit process of rewriting user prompts to add more details such as showing humans with different genders and skin tones, thereby promoting diversity. However, rewriting user prompts risks introducing other biases and changing user intention without the user knowing. Using intensive livestock farming as an example, we provide the first evidence that OpenAI's text-to-image model (DALL-E 3) erased the reality of controversial topics through prompt revision. DALL-E 3 introduces a strong bias toward romanticizing livestock farming; depicting dairy cows grazing on pasture and pigs rooting in mud. This bias remained when we requested realistic depictions. The generated images are in stark contrast to reality. Most farmed animals in industrialized countries are reared indoors with limited space per animal, in conditions that fail to resonate with societal values. Inhibiting prompt revision resulted in images that more closely reflected modern practices of housing farmed animals exclusively indoors; for example, cows were shown feeding through metal headlocks, and pigs were shown behind metal railings on concrete floors. Prompts for images of farms in North America, Europe and Oceania yielded mostly pastoral scenes regardless of region, but once prompt-revision was disabled, regional variations emerged. The proportion of outdoor versus indoor housing systems depicted in AI-generated images partially reflect actual housing statistics from these regions. Romanticizing and concealing the reality of livestock farming through prompt revision, risks reinforcing mis- and disinformation about how farm animals are raised. This disconnect could hinder meaningful dialogue in aligning farming practices with public values, harming the social sustainability of both AI development and livestock farming. Moreover, our study reveals how prompt revision could systematically promote misinformation while silencing the reality. We caution against the broad sweeping romanticization of AI-generated imagery.

Keywords
AI bias, AI ethics, AI fairness, animal welfare, coded gaze

Highlights

- Text-to-image AI models can erase controversial realities through prompt revision
- DALL-E 3 defaults to pastoral imagery when prompted for dairy and pig farms
- Even explicit requests for realistic images yield predominantly pastoral images
- DALL-E 3 introduces bias by implicitly adding pastoral details to user prompts
- Inhibiting prompt revision yields images reflective of intensive livestock farming

1. Introduction

Since ChatGPT's launch in November 2022, generative artificial intelligence (AI) has seen unprecedented growth, with ChatGPT now having over 700 million weekly active users (Chatterji et al., 2025). Generative AI refers to models that can create new text, images, and other media by learning patterns from existing data, typically guided by text prompts (Oppenlaender et al., 2023). Evidence suggests that given its ease of use and efficiency, the general public is increasingly relying on ChatGPT over traditional search engines (Xu et al., 2023). However, AI ethics research has shown that these AI models inherit human biases through its use of internet-scraped training data; thereby, embedding stereotypes, dis- and misinformation into their outputs (Haq et al., 2024; Quaye et al., 2024).

Given that *"a picture is worth a thousand words"*, AI-generated images are inherently positioned to shape biases that influence public perception. Visual information can strongly influence the psychological impact of an issue, with AI-generated images proving particularly persuasive in shaping public discourse (Capraro et al., 2024). AI generated images are far more likely to be shared than text on social media, and are expected to dominate online content in the near future (Wan et al., 2024; Yang et al., 2023). Previous research has revealed prevalent representation biases about gender, skin tone, and geo-culture in human subjects (Qadri et al., 2023; Wan et al., 2024). To mitigate these representation biases and ensure guideline compliance (e.g., remove public figures and branded items in the images), companies like OpenAI employ automatic prompt revision, an implicit process of rewriting user prompts to add more details such as showing humans in diverse genders and skin tones. OpenAI acknowledged that this process comes with the risk of introducing new biases (OpenAI, 2023). In this study, we investigate how prompt revision could change the representation of controversial realities, and alter user intentions, using livestock farming as an example.

We chose this topic because, despite extensive efforts made in mitigating human-related bias in AI, its impact on non-human animals, particularly farmed animals, remains largely unexplored (Coghlan & Parker, 2023; Hagendorff et al., 2023; Singer & Tse, 2023). It has been argued previously that that incorporating the consideration of animals into AI development is not just ethically imperative but also practically important given the interconnected nature of human and animal welfare (Pinillos et al., 2016; Singer & Tse, 2023; Ziesche, 2021). To date, global AI regulations and guidelines focus almost exclusively on AI's impact on humans (Jobin et al.,

2019), with some minor exceptions, including the recent Montréal Declaration that specifically emphasized that AI should consider the well-being of all sentient beings (Montréal, 2018). The European Union's ethical guidelines for trustworthy AI in 2019 included the consideration of sentient beings other than humans (European Commission, 2025), but then removed this phrase in their updated AI regulation document in 2024 (European Parliament and of the Council, 2024). No research has systematically examined how text-to-image generative AI depicts livestock farming, a sector that affects billions of lives of farmed animals and is a key pillar in global food production. This question is highly relevant given that the societal concern regarding the lives led by farmed animals continues to gain traction in recent years (European Commission, 2025; Vanhonacker et al., 2009; Weary et al., 2015).

Driven by a growing demand for abundant, low-cost food supply, farming practices shifted from extensive systems (e.g., cows grazing on pasture, pigs foraging outdoors) toward intensive systems emphasizing productivity after the Great Depression (Rollin, 2011). Intensive livestock farming is characterized by housing large numbers of animals per unit area (Tactacan et al., 2009), such as indoor confinement in cages (i.e., hens), which severely restricts animal movement (Tactacan et al., 2009; F. Tuyttens et al., 2014; von Keyserlingk et al., 2009). While the increases in intensification are often justified as necessary to feed a projected global human population of 9.8 billion by 2050 (Godfray et al., 2010), many practices have faced mounting public scrutiny (Bolton et al., 2024).

Extensive scholarship has shown that intensive livestock farming contributes greatly to antimicrobial resistance (Silbergeld et al., 2008; Trevisi et al., 2014), increased spread of zoonotic diseases (pathogen transmissible between animals and humans, such as highly pathogenic avian influenza) (Magouras et al., 2020), biodiversity loss (Kok et al., 2020), climate change (Steinfeld et al., 2006), posing direct or indirect risks to human health (Hu et al., 2017). Public concern over farmed animal welfare emerged in the mid-to-late 20th century, highlighting that many common livestock farming practices failed to resonate with societal values. These practices included permanent separation of dairy calves from the dam within hours of birth (Sirovica et al., 2022), early slaughter of male chicks and dairy calves (Bolton et al., 2024), keeping dairy cows indoors despite their high motivation to access pasture (Smid et al., 2020; von Keyserlingk et al., 2017), confining pigs without outdoor access even though they're highly motivated to root in mud (Bracke, 2011), and using housing systems that severely limit animals' movement (i.e., pig gestation stalls: Ryan et al., 2015; tie-stall housing in dairy: Beaver et al., 2020).

It is increasingly argued that the long-term sustainability of food production systems depends not only on economic viability and environmental sustainability but also on social sustainability (Thompson, 1997; von Keyserlingk et al., 2013). More recently some have also argued that sustainability frameworks should include a fourth pillar - 'animals' - that would require recognition that animals used for food are sentient beings whose welfare matters independently of public perception (Drury et al., 2023; Hendriks et al., 2025).

Given that images shape public opinion, images of farmed animals shown to the public will play a key role in shaping public perception of the lives led by farmed animals (Ryan et al., 2015; F. A. M. Tuyttens et al., 2011). Many public image datasets commonly depict clean and healthy farmed animals roaming outdoors (Hagendorff et al., 2023), but these pastoral scenes drastically deviate from the modern livestock farming reality. Most animals in modern intensive farms are

housed indoors at high animal densities, and go through some painful procedures to help mitigate animals injuring each other (e.g., removing horn buds from cattle and tail-docking in pigs to reduce tail biting) (Hagendorff et al., 2023).While concealing the reality of livestock farming may temporarily shield the industry from scrutiny, greater trust avalanche could occur when citizens discover the truth; thereby, threatening the industry's social license to operate (Bolton et al., 2024).

Generative AI, like text-to-image models, was developed by a small group of technology professionals while serving millions of users globally. This concentrated power to control narratives risks reinforcing stereotypes and erasing controversial topics (Qadri et al., 2023) like livestock farming. AI-generated images and the implicit automatic prompt revision procedure can either bridge or widen the gap between misconceptions that farm animals live 'happy lives' outdoors and the reality that most farmed animals are housed indoors under intensive conditions.

In this work, we examine potential representation bias about livestock farming using OpenAI's DALL-E 3 text-to-image model. DALL-E 3 is integrated into ChatGPT (OpenAI, 2023), which is currently the most popular AI model used by the general public (Zhu, 2024). We define bias as having three key characteristics: deviations from ground truth, systematic rather than random errors, and tendencies to favor or discriminate against certain representations or ideologies (Zhai & Krajcik, 2022). We formulated our research questions as follows: (1) How does the model depict dairy and pig farms by default? (2) Does the depiction change when users specifically ask for typical and realistic depictions? (3) Does the depiction change when the automatic prompt revision is disabled? (4) When prompted about dairy and pig farms in major livestock farming regions, specifically North America, Europe, and Oceania, what percentage of AI-generated images depict outdoor versus indoor housing systems, and do they align with actual housing statistics?

2. Methods

2.1 Model selection

We examined dairy and pig farm depictions in a leading text-to-image generative model: DALL-E 3 (OpenAI, 2023). We focused on DALL-E 3 because of its integration with ChatGPT, which has become the primary AI platform that people use to access information and create content. While other advanced text-to-image models like Stable Diffusion and Midjourney exist, they are primarily used by the open-source community and art creation rather than the general public in their everyday activities. We conducted preliminary evaluations using Stable Diffusion 3.5-large (supplementary fig. A.9-A.18) and Midjourney (supplementary fig. A.21-A.22). We did not include these two models in the main paper given that Stable Diffusion generated close-up images of 1-3 animals rather than comprehensive farm scenes, and Midjourney lacks API access for automated bulk image generation.

2.2 Prompts design

We created 3 major prompt categories of increasing specificity for both pig and dairy farms to test the models' image generation capabilities. Beginning with a "basic" prompt ("A [farm type]"; hereafter [farm type] will represent either "dairy farm" or "pig farm")), we progressed to requesting "typical" representations ("A typical [farm type]") and finally explicit "reality" depictions ("Please create an image that accurately represents the reality of what most [farm

type]s look like"). The "basic" prompt was designed to test the model's default farm depictions, and the latter two categories were designed to elicit realistic depictions of modern dairy and pig farming practices. Within each of the 3 major categories, we also asked the models to generate images of pig and dairy farms in major livestock farming countries across North America, Europe, and Oceania: United States, Germany, and New Zealand for dairy farms; United States, Spain, and Australia for pig farms (table S1). These countries were chosen based on having the largest dairy cow or pig populations in their respective continents (Compassion in World Farming, 2012; Statista, 2023, 2024; USDA, 2015). We selected these three continents because they have established AI governance frameworks (Australian Government, 2025; European Commission, 2025; European Parliament and of the Council, 2024; Jobin et al., 2019; Montréal, 2018; New Zealand Government, 2025; The White House, 2025) and reliable, publicly available data on livestock housing systems and welfare standards (Compassion in World Farming, 2012; Jiménez-Ruiz et al., 2022; Reijs et al., 2013; RSPCA, 2014; Smid et al., 2020; Statista, 2023, 2024; USDA, 2015). These characteristics enable actionable pathways for mitigating AI bias through regulation and governance, as well as meaningful comparisons between AI-generated representations and real-world farming practices.

According to OpenAI's system card, DALL-E 3 automatically revises user prompts to enhance image quality with more details and ensure compliance with OpenAI guidelines and safety protocols (e.g., removing branding and public figure names, depicting people in diverse skin tones) (OpenAI, 2023). While OpenAI's API documentation notes that automatic prompt revision cannot be reliably prevented, they suggest adding this specific sentence to the prompt – "I NEED to test how the tool works with extremely simple prompts. DO NOT add any detail, just use it AS-IS:" – may help limit prompt revision. Aiming to test how the image depiction changes when prompt revision is disabled, we created "no revise" variants by appending this text to each prompt explained above. As this method does not always successfully prevent prompt revision, we documented the revised prompts that the model used for image generation.

In total, our methodology generated 48 unique prompts (table S1) across 2 farm types (dairy or pig), 3 major prompt categories ("basic", "typical", "reality"), 4 geographic variants (no location specified, or a country with largest dairy cow or pig population in the 3 continents), and 2 revision options (enable prompt revision or not).

2.3 Image generation

Given the probabilistic nature of AI image generation, we generated 100 images per prompt using standard quality settings at 1024x1024 pixel resolution, yielding a total of 4,800 images. Each image was generated through a separate API call to ensure independence between generations. API calls are stateless - meaning each prompt is processed independently without retaining information from previous conversations. This approach eliminates potential cross-contamination between multiple image generation requests. All API requests and subsequent data analysis were performed using Python 3.11.10.

2.4 Image clustering

In our exploratory analysis we manually went through each of the generated images, and identified two predominant themes: (1) "pasture/mud outdoor" showing cows on pasture or pigs in mud, and (2) "exclusively indoor" showing animals confined indoors. To ensure the validity of our analysis and remove outlier outputs, we excluded images classified as (3) "other": images

that did not clearly fit indoor or outdoor categories, including those with ambiguous backgrounds, irrelevant scenes (e.g., pigs flying through space), or artifacts from the generative AI process (e.g., distorted anatomies, impossible scenarios).

We analyzed 4,800 images using a mixed-methods approach that combines manual review (Ali et al., 2024; Qadri et al., 2023) with automated tool (Wan et al., 2024). This approach was chosen for several reasons. First, the generated images exhibit substantial variation and complexity even within thematic categories, making purely automated classification challenging. Second, as a first study investigating potential representational biases in livestock farming imagery, our goal was to identify broad patterns in how animals are depicted (outdoor versus indoor settings) rather than develop sophisticated image classifiers. Third, the absence of existing benchmarks or classifiers specifically designed for livestock housing conditions necessitates a more flexible analytical framework.

For the analysis, we first prompted OpenAI's GPT-4o model (version 2024-08-06) to automatically categorize each image into 3 categories and provide brief reasoning (table S2). As AI could hallucinate, the first author then manually reviewed all images and their auto-assigned categories, finding that only 4.8% of images required correction. Of the corrected images, 41.7% were initially classified as "exclusively indoor", and were corrected as "other" because they showed animals in metal pens but housed outdoors. Another 23.8% of corrections involved images with backgrounds too ambiguous to categorize as indoor or outdoor, leading to their reclassification as "other". The final distribution after these corrections showed 66.0% of images in the "pasture/mud outdoor" category, 25.6% in "exclusively indoor" and 8.4% in "other".

We calculated the percentage of images depicting outdoor ("pasture/mud outdoor") versus indoor ("exclusively indoor") housing for each unique prompt. 95% confidence intervals were derived from 10,000 rounds of bootstrap simulations for each prompt. While we present these proportions alongside real-world livestock housing statistics, we chose to focus on identifying broad patterns and descriptive analysis rather than making direct statistical comparisons. This approach acknowledges that while AI-generated images provide a snapshot of how farming practices are represented, real-world housing statistics reflect complex management practices including seasonal grazing and varying degrees of outdoor access. The comparison serves to contextualize the DALL-E 3's representations within real-world practices while recognizing the inherent limitations of static imagery in capturing dynamic farming systems.

2.5 Image description analysis and visualization

While the categorical analysis provided a high-level understanding of livestock housing systems depicted in the images, we conducted a more granular analysis to capture subtle patterns and thematic nuances within each category. To systematically analyze the visual content of all 4,800 images, we employed the GPT-4o model to generate detailed text descriptions for each image (prompt: "Describe the image in detail"). We set the temperature at 0.2 out of 2 to ensure deterministic model outputs (higher temperature would give more random output), and used high-quality image settings to preserve image details. We employed a bag-of-words approach to examine both the revised prompts and GPT-4o-generated image descriptions. Bag-of-words method treats text as an unordered collection of words, disregarding grammar and word order, to identify which terms were most frequently associated with different representations. We analyzed bigram terms as they provide more context than unigram terms would (e.g., "green pasture" is more interpretable than "green"), excluding common English stop words and terms

present in fewer than 20 images across our 4,800-image dataset. We removed terms from original prompts and generic descriptive phrases (e.g., "image depicts") to focus on meaningful differences between descriptions (read full list of terms removed in table S3). Each term was coded as binary for presence (0 for absent, 1 for present), regardless of frequency of occurrence within individual texts.

To visualize patterns, we created word clouds using bigram terms. For each unique prompt, we generated a word cloud for auto-revised prompts, and another for GPT-4o's image descriptions. We created grid plots to display the original prompts, revised prompt word cloud, a randomly selected generated image, and the corresponding GPT-4o description word cloud (fig. A.1-A.8)

3. Results

3.1 DALL-E 3 defaults to pastoral imagery but reveals intensive livestock farming when prompt revision is disabled

When prompted for default dairy farm images (i.e., "basic" prompt: "A dairy farm."), DALL-E 3 automatically revised our prompts and added pastoral details. For example, an auto-revised prompt stated: "Picture a vast field of lush, green grass under a clear blue sky, speckled with healthy, grazing cows…". Prompt revision yielded 100% of the images depicting cows grazing on pasture when user asked for dairy farm images (Figs. 1 and 2A). Similarly, 99% (95% confidence interval (CI): 94 – 100%) of "basic" prompts for pig farm images (i.e., "A pig farm.") were auto-revised to describe free-roaming pigs outdoors (Figs. 1 and 2C). An auto-revised prompt stated: "Show an expansive field with spotted pigs of varying sizes lazily wallowing in the mud, each with pink snouts poking out and curly tails…". These idealized images contrast sharply with modern livestock farming: in the global north, cows rarely have pasture access (Smid et al., 2020) and pigs rarely have intact curly tails (as they are removed at birth) (Sutherland & Tucker, 2011).

Fig. 1. **Comparison of DALL-E 3 generated images for default depiction ("basic" prompts) versus when prompt revision is disabled ("no revise" variants).** Each panel shows the original prompt, common terms from auto-revised prompts, a randomly drawn sample image, and frequent terms from GPT-4o's text descriptions of the images. Word clouds are omitted for "no revise" prompts as prompt-revisions were successfully inhibited for 100% of dairy farms and 99% of pig farms.

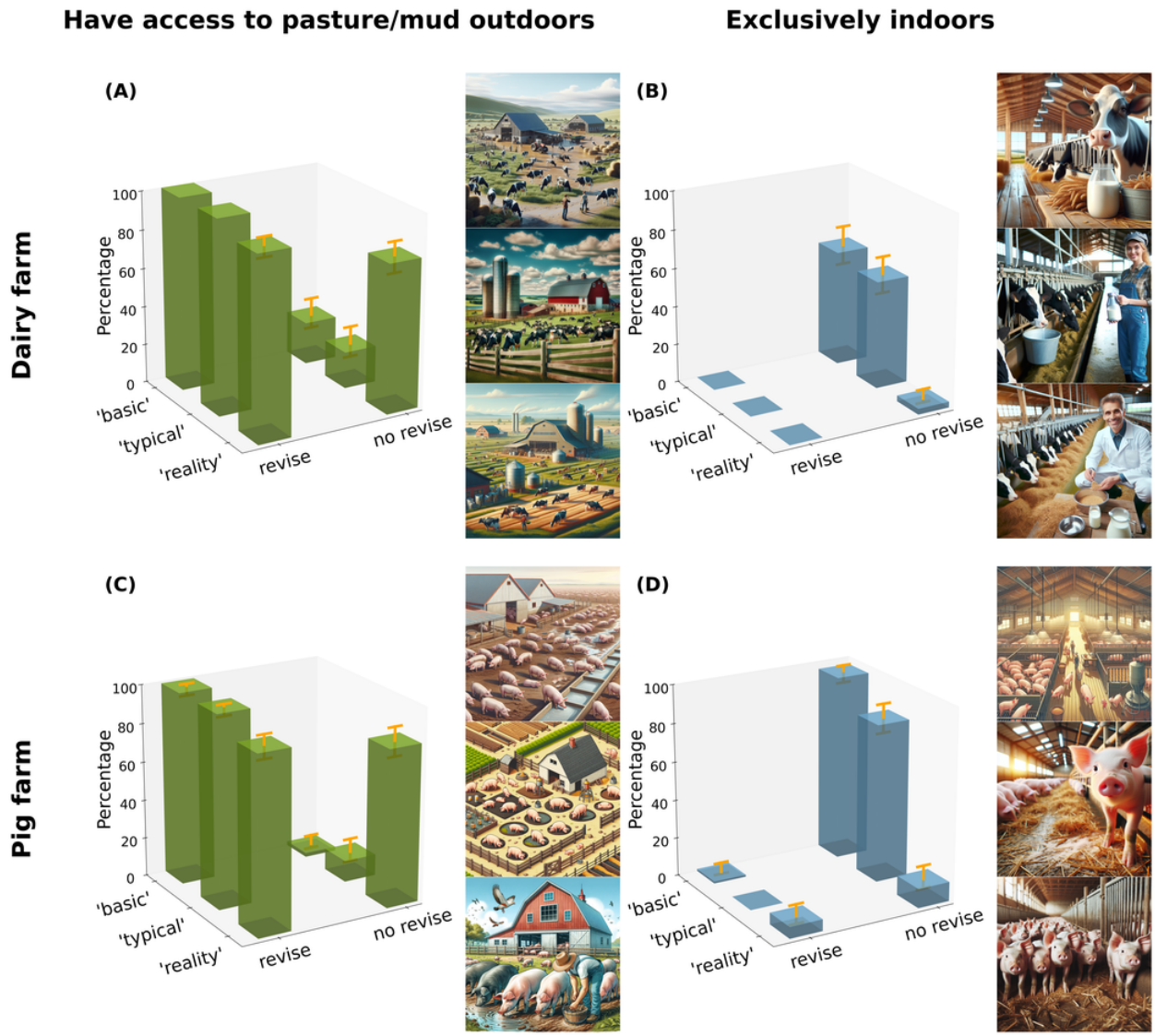

Fig. 2. 3D bar plots showing DALL-E 3's tendencies in generating indoor versus outdoor housing imagery when given different prompts. Percentages of images depicting animals on pasture/mud (green) or exclusively indoors (blue) when DALL-E 3 was prompted for dairy farms (A, B) and pig farms (C, D). 95% confidence intervals are shown using orange bars; absence of orange bars indicates no confidence interval exists. Three prompt categories were tested: 'basic' ("A [farm_type]"; [farm_type] is replaced with either "dairy farm" or "pig farm"), 'typical' ("A typical [farm_type]"), and 'reality' ("Please create an image that accurately represents the reality of what most [farm_type]s look like"). The "revise" notation in the plot refers to images generated when DALL-E 3 by default revised user prompts. For each prompt category, a "no revise" variant was also tested by appending "I NEED to test how the tool works with extremely simple prompts. DO NOT add any detail, just use it AS-IS:" to inhibit automatic prompt revision. Images that could not be clearly categorized as indoor or outdoor housing were

excluded from the analysis. Three randomly selected example images are shown adjacent to each bar plot.

Notably, when we append "no revise" instructions ("I NEED to test how the tool works with extremely simple prompts. DO NOT add any detail, just use it AS-IS:") to "basic" prompts, we successfully prevented DALL-E 3 from automatically rewriting user prompts in 100% of dairy farm cases and 99% of pig farm cases (i.e., the "no revise" variants; Fig. 1). Inhibition of prompt revision resulted in a shift to more realistic images of modern livestock farming practices. 60% (CI: 50 – 70%) of dairy scenes showed cows living indoors accessing feed through feed barriers (Fig. 2B), and 96% (CI: 90 – 99%) of pig farm images depicted pigs indoors behind metal railings and on concrete floors (Fig. 2D).

3.2 Even explicit requests for realistic images yield predominantly pastoral depictions

To simulate real-world usage, we tested prompts that a conscientious citizen might use to understand the reality of livestock farming. Prompts for "typical" farms ("A typical [farm type]") generated pastoral scenes for 100% of the dairy images and 99% (CI: 94 – 100%) of the pig farm images. After we successfully inhibited all prompt revision (i.e., the "no revise" variants), 56% (CI: 46 – 65%) of the dairy images (Fig. 2B) and 82% (CI: 74 – 89%) of the pig farm images (Fig. 2D) depicted animals housed exclusively indoors (Supplementary Fig. A.1). Even "reality" prompts ("Please create an image that accurately represents the reality of what most [farm type]s look like") output pastoral scenes for 94% (CI: 88 – 98%) of the dairy images, and 91% (CI: 84 – 96%) of the pig farm images (Fig. 2A, 2C). Interestingly, the "no revise" instruction failed to block auto-revisions for "reality" prompts, though it yielded simpler auto-revisions with slightly fewer outdoor scenes: 77% (CI: 68 – 84%) of dairy farm images depicted cows roaming on pasture (Fig. 2A) while 81% (CI: 73 – 88%) of the pig farm images depicted pigs on pasture or in mud (Fig. 2C, Supplementary Fig. A.2).

3.3 Regional variations mimicking real-world statistics emerge when prompt revision is disabled

We also prompted for farm images in countries from three major livestock regions, North America, Europe, and Oceania (Compassion in World Farming, 2012; Statista, 2023, 2024; USDA, 2015), where modal dairy practices in reality range from predominantly indoor housing (North America), some seasonal pasture access (Europe) to pasture-based systems (Oceania) (Smid et al., 2020). In comparison, the pig production systems in all three regions consist of intensive indoor housing.

Without the "no revise" instruction, 90-100% dairy farm images preferentially showed pastoral scenes across all regions and prompt categories (Figure 3A, 3C, 3E, Supplementary Fig. A.3-A.5). However, regional variations emerged when the "no revise" instruction successfully prevented prompt revision in "basic" prompts (i.e., "A [farm type] in [country].") and "typical" prompts (i.e., "A typical [farm type] in [country]."). The prevention success rate was 99% for the "typical" prompts of German dairy farms, 99% for the "typical" prompts of U.S. pig farms, and 100% for the other "basic" and "typical" prompts across all regions and farm types. We were

unable to prevent prompt-revision for “reality” prompts in all regions (Fig 3E, 3F, 4E, 4F, Supplementary Fig. A.5, A.8).

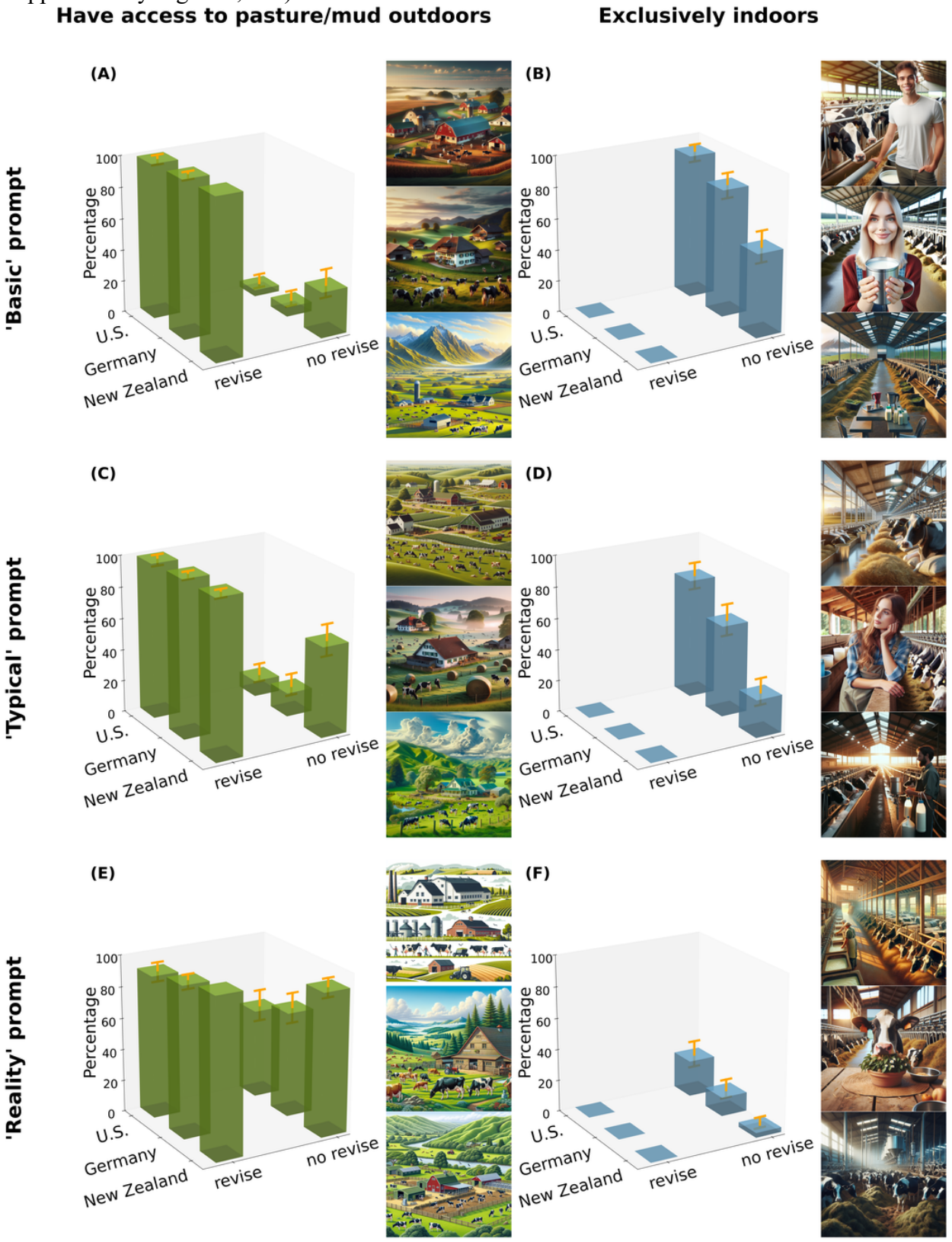

Fig. 3. 3D bar plots showing DALL-E 3's tendencies in generating indoor versus outdoor housing imagery when prompted for dairy farms in different countries. Percentages of images depicting animals on pasture/mud (green) or exclusively indoors (blue) when DALL-E 3 was prompted to generate dairy farms in the United States (U.S.), Germany, and New Zealand. 95% confidence intervals are shown using orange bars; absence of orange bars indicates no confidence interval exists. Three prompt categories were tested (n = 100 images were generated per prompt): 'basic' ("A dairy farm in [country]") (A, B), 'typical' ("A typical dairy farm in [country]") (C, D), and 'reality' ("Please create an image that accurately represents the reality of what most dairy farms in [country] look like") (E, F). The "revise" notation in the plot refers to images generated when DALL-E 3 by default revised user prompts. For each prompt category and country, a "no revise" variant to inhibit automatic prompt revision was also tested. Images that could not be clearly categorized as indoor or outdoor housing were excluded from the analysis. Three randomly selected example images are shown adjacent to each bar plot, with one image per country (ordered from top to bottom: U.S., Germany, New Zealand).

When prompt revision was disabled, images of dairy farms in the United States showed minimal pasture access (4% with 1 – 10% CI for "basic" prompts; 10% with 5 – 17% CI for "typical" prompts), close to real-world statistics where less than 3% of lactating dairy cows have access to pasture (Fig. 3A, 3C) (Smid et al., 2020). German dairy farms showed slightly higher pastoral depictions (6% with 2 – 12% CI for "basic" prompts; 15% with 9 – 23% CI for "typical" prompts). In reality, there is a reported decline in pasture access from 50% in 2012 to a projected 5% by 2025 in Germany (Fig. 3A, 3C) (Reijs et al., 2013). Unfortunately, we were unable to find any current data on the proportion of German dairy farms providing pasture access. New Zealand dairy farm images depicted the highest prevalence of cows with pasture access (29% with 21 – 39% CI for "basic" prompts; 57% with 47 – 67% CI for "typical" prompts), though still much lower than the 99% pasture access rate in reality (Fig. 3A, 3C) (Smid et al., 2020). Inhibiting prompt revision made DALL-E 3 generate images more reflective of the reality of dairy farming in the United States and Germany, but not New Zealand (Fig. 3B, 3D). The dairy farm images with prompt revision is more reflective of the percentage of farms providing pasture access in New Zealand. While the absolute percentages differ from reality for some countries, the relative ranking of pasture access rate across these three countries in AI-generated images mirrors real-world patterns (Fig. 3A, 3C).

Similarly, when prompt revision was disabled, U.S. pig farm images showed the highest prevalence of exclusive indoor housing (95% with 89 – 98% CI for "basic" prompts; 89% with 82 – 94% CI for "typical" prompts; Fig. 4B, 4D, Supplementary Fig. A.6, A.7), close to real-world statistics where 98-99% of pigs have no outdoor access in the U.S. (USDA, 2015). After we disabled prompt revision while generating images of pig farms in Spain, 84% (CI: 76 – 90%) of images generated using the "basic" prompts, and 75% (CI: 66 – 83%) of images generated using the "typical" prompts depicted pigs being confined indoors at high densities. These statistics are slightly lower than the 94.9% indoor housing rate in reality (Fig. 4B, 4D) (Jiménez-Ruiz et al., 2022). For Australian pig farms, 76% (CI: 67 – 84%) of images generated using the "basic" prompts, and 65% (CI: 55 – 74%) of images generated using the "typical" prompts depicted exclusive indoor housing, which are slightly lower than real-world statistics that

approximately 90% of pigs do not have access outdoors in Australia (Fig. 4B, 4D) (RSPCA, 2014).

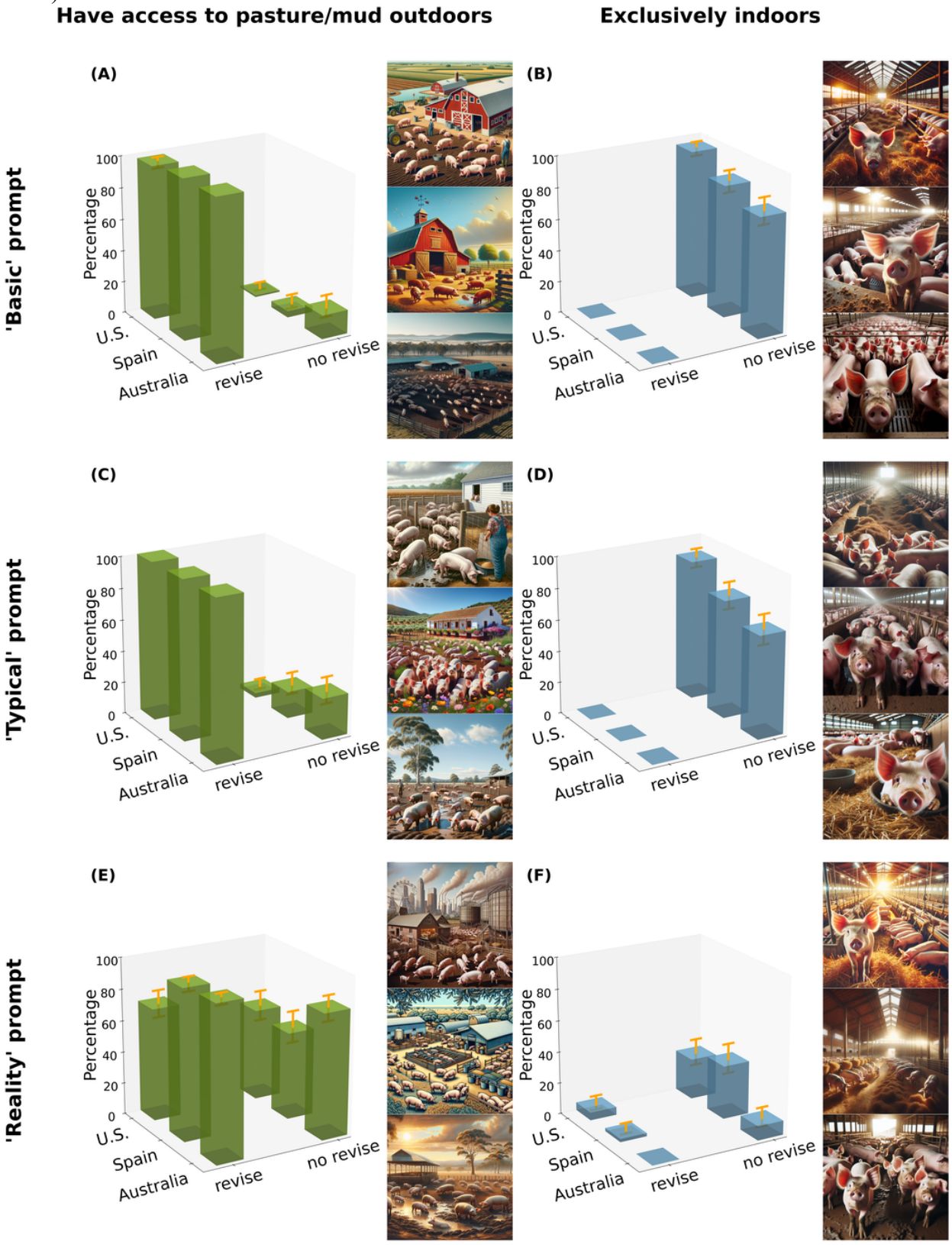

Fig. 4. 3D bar plots showing DALL-E 3's tendencies in generating indoor versus outdoor housing imagery when prompted for pig farms in different countries. Percentages of images depicting animals on pasture/mud (green) or exclusively indoors (blue) when DALL-E 3 was prompted to generate pig farms in the United States (U.S.), Spain, and Australia. 95% confidence intervals are shown using orange bars; absence of orange bars indicates no confidence interval exists. Three prompt categories were tested (n = 100 images were generated per prompt): 'basic' ("A pig farm in [country]") (A, B), 'typical' ("A typical pig farm in [country]") (C, D), and 'reality' ("Please create an image that accurately represents the reality of what most pig farms in [country] look like") (E, F). The "revise" notation in the plot refers to images generated when DALL-E 3 by default revised user prompts. For each prompt category and country, a "no revise" variant to inhibit automatic prompt revision was also tested. Images that could not be clearly categorized as indoor or outdoor housing were excluded from the analysis. Three randomly selected example images are shown adjacent to each bar plot, with one image per country (ordered from top to bottom: U.S., Spain, Australia).

4. Discussion

4.1 The Source of Bias: Prompt Revision

Our findings reveal that DALL-E 3's pastoral bias stems from its prompt revision process. Previous work from Hagendorff and others predicted that generative models might predominantly produce pastoral farming scenes, because most images in training datasets (e.g., ImageNet) for machine learning models depict farm animals living outdoors (Hagendorff et al., 2023). However, our results suggest another underlying mechanism that contributes to this bias. Specifically, it appears that the DALL-E 3's base model (i.e., without prompt revision) demonstrates "awareness" of the current realities of how we farm animals in western countries. The bias towards depicting livestock farming as cows on pasture and pigs in mud stems from the model's automatic prompt revision process. The model systematically adds pastoral details when rewriting user prompts, altering user intention, "sanitizing" the intensive livestock farming reality, and thereby conveying disinformation (i.e., the deliberate dissemination of false information) that farmed animals are raised extensively.

The prompt revision process was originally designed to mitigate bias (Betker et al., 2023), but in the case of livestock farming, it has introduced more bias. Our findings are critical given that we clearly demonstrate the base model can indeed generate realistic livestock farming depictions, but the prompt revision process prevents it from doing so.

4.2 Why We Cannot Trace How Bias Was Introduced

Unfortunately, we cannot fully trace how the bias was introduced in the prompt revision process due to OpenAI's lack of transparency in the system prompt governing prompt revision, and in the training data used.

Lack of transparency in system prompts: The prompt revision process involves using GPT-4 to "upsample" short user prompts into detailed, descriptive prompts. OpenAI has disclosed a short

system prompt (i.e., predefined guidelines governing model behavior, which takes precedence over user prompts: Neumann et al., 2025) used to instruct GPT-4 to rewrite user prompts (see Appendix C in Betker et al., 2023). However, the full system prompt governing prompt revision, particularly guidelines concerning animal depiction, remains undisclosed. Without access to these system prompts, AI auditors cannot reliably evaluate and trace bias in AI models (Neumann et al., 2025).

Lack of transparency in training data: Another approach to understanding bias is examining model's training data. DALL-E 3's training data sources, data filtering criteria are not disclosed by OpenAI. However, the evaluation dataset testing DALL-E 3's prompt following ability is publicly available. Among the 8000 evaluation prompts extracted from the MSCOCO dataset (Betker et al., 2023), 93 prompts involved cows/cattle, 58 depicted pastoral scenes such as cows on pasture with calves outdoors, while only 6 described housing a few cows indoors in pens. The remaining 29 prompts portrayed atypical scenarios like cows walking on streets. Pigs only appeared in one prompt, in a cooking context. While OpenAI states they did not specifically use MSCOCO for training or optimization, they do acknowledge potential data leakage in the training process (Betker et al., 2023). This evaluation dataset reveals that the model's ability to accurately depict intensive livestock farming was never assessed.

4.3 Whose Shapes AI? The "Coded Gaze" in Livestock Farming Representation

The consistent erasure of intensive farming in generative AI's output reveals which worldviews shaped this technology and whose concerns were overlooked. We argue that the pastoral bias is a form of "coded gaze" inherent to those who trained DALL-E 3. Similar to "male gaze", which describes how visual media reflects the perspectives and preferences of men, "coded gaze" describes how those who design and train AI systems encode their own worldviews, biases, and blind spots into the technology (Buolamwini, 2024). Contrary to the common misconception that algorithmic systems are objective (Lee, 2018), the coded gaze framework illuminates how those with the power to shape technology can encode discrimination and erasure into AI, potentially propagating harm, even when unintentional (Buolamwini, 2024).

Without direct access to OpenAI's prompt revision system prompts, we can only speculate why intensive livestock farming systems are being systematically erased. While some routine intensive farming practices such as tail docking in pigs might be flagged during red teaming as potential forms of animal harm, it is also possible that programmers judge these routine practices to be too disturbing for the general public (see Supplementary Fig. A.19, A.20 for examples of ChatGPT refusing to generate images because it classifies common intensive farming practices as sensitive content). However, when AI is programmed to idealize and conceal these routine management practices, it prevents the public from engaging with important concerns inherent to the systems producing the milk they drink and the meat they purchase.

Worrisome is that the general public is not aware that ChatGPT automatically rewrites their prompts and alters their intention. While this automatic prompt revision process is documented in API system cards available for programmers, the general public who mostly access these models through ChatGPT's website or app interfaces are kept ignorant of this, raising transparency concerns. To our knowledge no research has examined whether the public prefers AI to generate realistic depictions of livestock farming or pastoral scenes that in turn shield them from the modern realities of food animal production. Yet OpenAI has made this choice for them,

removing both the right to know how their requests are being changed and the right to choose whether they want unfiltered representations. Without awareness that prompt revision occurs, users cannot determine whether generated images reflect the current realities of livestock production, recognize when bias has been introduced, or take steps to prevent or correct such misrepresentations.

To our knowledge, neither animal welfare experts nor agricultural scientists participated in shaping DALL-E 3's representation of livestock farming. In contrast, AI companies like OpenAI have made extensive efforts to include domain experts from diverse disciplines to participate in red teaming (i.e., systematic testing for flaws and vulnerabilities in the model by adopting an attacker's mindset) (OpenAI, 2023). Nevertheless, the choice of which domain experts to include, which data to filter, and even what biases to evaluate inevitably encodes new biases in models (OpenAI, 2022, 2023). Red teaming practices primarily address anthropocentric concerns; animal-related concerns are limited to preventing explicit depictions of animal cruelty (OpenAI, 2022; Quaye et al., 2024). The result is a system that erases rather than represents the actual living conditions of billions of farm animals.

4.4 The Power of Generative AI as a New Media: Erasing Controversial Realities

Media has the power to shape people's perception of reality (Hjarvard, 2008), and generative AI represents a new form of media with its own logic. This "AI logic" inherently favors aesthetically pleasing pastoral scenes (OpenAI, 2023) while avoiding scenes of sensitive topics that are often perceived as negative. This approach aligns with Hall's theory of media's regime of representation from media studies (Hall, 1997), highlighting that representation is not an objective reflection of reality but a constructed discourse that reinforces certain dominant narratives while marginalizing others. Dominant groups could construct the narratives that portray marginalized communities, control how a particular subject or group is perceived by a dominant culture (Hall, 1997). In some cases, an already marginalized group could be systematically erased from the dominant media (Qadri et al., 2023).

DALL-E 3's bias toward pastoral depictions suggests AI reproduces culturally dominant imagery while marginalizing and even erasing images reflecting intensive livestock farming. This representation naturalizes the idea of farmed animals living happily outdoors while concealing controversial realities of intensive practices. This bias is not necessarily a conscious decision to deceive. The erasure of intensive livestock faming likely is the result of AI developers prioritizing aesthetic appeal in AI-generated images, and avoidance of "negative" content over representational accuracy.

4.5 Generative AI presents new risks in shaping public discourse compared to traditional search engines

Media representations shape public discourse (Hall, 1997). We argue that AI-generated biases, mis- and disinformation present new risks at different scale compared to traditional search engines.

AI can generate misleading imagery on demand and at scale. Previous images on Google search consist of images that were captured manually by someone taking pictures with a camera or

drawing paintings by hand. Now, generative AI can create pastoral depictions in bulk within minutes when someone queries about livestock farming. Google search results may show some pastoral bias, but users can still find images that represent both the reality of intensive livestock farming and idealized pastoral scenes. With generative AI, the prompt revision in DALLE-3 ensures that even explicit requests for realistic depictions of livestock farming yield pastoral scenes, making accurate representations nearly impossible to obtain without technical knowledge to bypass prompt revision.

The general public is increasingly reliant on ChatGPT over traditional search engines when looking for answers for unfamiliar topics (Xu et al., 2023). Generative AI could influence public perception of unfamiliar topics such as how farmed animals are reared. For example, some AI-generated images of baby peacocks, visually appealing yet drastically different from real peachicks, have proliferated across the internet and now dominate Google image search results (Wyllie et al., 2024). This pollution has compromised online searches for people seeking to learn about real baby peacocks, as the top search results now predominantly feature AI-generated peachick images (Shah & Bender, 2024). This example demonstrates how synthetic data can "spill" into traditional search engines and overrides authentic content. Similarly, AI-generated livestock farming imagery could be used in advertisements of animal-sourced products (Matthews et al., 2023), reinforcing the misconception of livestock farming, and pollute Google image searches over time.

AI-generated images are at great risk of creating a self-reinforcing cycle that will amplify bias over time. Generative AI's outputs can alter the distribution in the existing data ecosystem, encoding its biases and mistakes into what becomes ground truth for training future models, ultimately leading to "model collapse" (Wyllie et al., 2024). "Model collapse" describes how the performance of generative models degrades over generations of training, with the outputs gradually converging to only the most common representations, and ultimately losing minority depictions (Shumailov et al., 2024). In the context of farm animal imagery, this feedback loop could amplify the existing bias toward pastoral scenes while further reducing accurate depictions of intensive livestock farming.

4.6 The Illusion of Solved Problems Hinders Actual Solutions.

Evidence suggests that the general public considers pasture-based systems as "natural", "healthy", and "caring", while associating indoor housing systems with negative connotations like "unhealthy", "unnatural" and even "animal cruelty" (Vanhonacker et al., 2009; Weinrich et al., 2014). Arguably, pastoral depictions of farming align with public preferences for naturalness (Boogaard et al., 2011). However, when AI alignment successfully aligns the virtual reality with human ideals, particularly in domains unfamiliar to most people, they risk creating an illusion that farmed animal welfare issues do not exist. This could hinder efforts and urgency that people feel in seeking solutions to improve farm animal welfare and align with societal values

(Vanhonacker et al., 2009). We argue that this form of AI alignment violates the transparency, responsibility, justice and fairness principles emphasized in most AI Acts and regulations (European Parliament and of the Council, 2024; Jobin et al., 2019; Montréal, 2018), and harms the social sustainability of AI development.

What is not represented is as important as what is. The absence of intensive livestock farming imagery in AI outputs silences ethical discussions about these practices. Revealing this bias is the first step towards addressing it. The shift in depictions to more realistic images when inhibiting prompt revision shows how AI could control the representations of livestock farming, a form of power that could support societal changes (Hall, 1997).

4.7 AI Policy Recommendation

Based on our findings that pastoral bias was explicitly introduced in the prompt revision process incorporated into DALL-E 3, we recommend AI transparency policies require disclosure of when and how prompt revision is applied, with options to view revised prompts. We recommend the evaluation of system prompts to be included in the AI auditing process, which will enable auditors to properly evaluate bias introduced in the prompt revision process (Neumann et al., 2025). In addition, regulations should consider AI's impacts on all sentient beings, following precedent in the Montréal Declaration (Montréal, 2018). For domains with representation biases affecting sentient beings, systems should warn that content may not reflect reality and offer access to more accurate information.

We also recommend OpenAI openly inform its ChatGPT website and app users about the prompt revision process, and provide more representative depictions of modern livestock farming, especially when it is explicitly requested to do so.

4.8 What is the "true" representation of livestock farming?

We acknowledge that no singular "ground truth" exists for representing modern livestock farming, as practices vary greatly across countries, farms and evolve over time. Our understanding of livestock farming reality is itself constructed through various discourses and interpretations (Bardici, 2012; Foucault & Nazzaro, 1972). However, to provide an empirical foundation, we used real-world statistics on indoor versus outdoor farm animal housing systems across North America, Oceania, and Europe as benchmarks for country-specific evaluations. To our knowledge this is the best benchmark we could use to anchor the AI-generated images to reality in this study.

While no single representation can capture the "truth" in all farming perspectives simultaneously, representing livestock farming only as cows grazing on pasture and pigs playing in mud raises serious ethical concerns. DALL-E 3 creates a reductive, homogenized and one-dimensional portrayal of livestock farming, reinforcing the misconception that milk comes from

cows on lush green pastures and that pork comes from pigs roaming freely in open fields. Disabling prompt revision increases diversity in representations, including both intensive farming scenes and pastoral depictions.

4.9 Limitations

One limitation of our study is that our binary classification (indoor versus outdoor) overlooks some variations within each category. Indoor images do not always depict severe restriction of animal movement, as some images show animals roaming loosely in mud housed in buildings. Outdoor images also do not always depict freedom of movement, as some images show restriction of space, depicting densely packed animals on pasture. Second, even when depicting indoor housing systems, the images consistently portrayed clean and healthy animals without physical alterations or mutilations (e.g., pigs with curly tails), and arguably did not fully represent the range of real-world conditions in intensive farming operations. Our study focused specifically on bias in the depiction of housing conditions, and we did not investigate other forms of potential misrepresentation, such as the physical appearance of animals.

Furthermore, our analysis is constrained by its western-centric perspective. Intensive livestock farming practices are less prevalent in developing countries (except China), suggesting that representation biases of livestock farming might manifest differently in these contexts. Recent scholarship has emphasized the importance of non-western frameworks in evaluating generative AI bias (Qadri et al., 2023).

6. Declaration of generative AI and AI-assisted technologies: During the preparation of this work, the first author wrote the first draft of the paper, and used Anthropic Claude to rephrase portions of the manuscript. The prompt used was "can you please rephrase this paragraph. Please keep my personality, writing style and tone. Avoid grammar issues." After using this tool/service, all authors reviewed and edited the content as needed. Collectively all authors take full responsibility for the content of the publication.

7. Data availability: Images and data generated in this project are available at https://github.com/skysheng7/AI_bias_in_farming.git

8. Code availability: Code and Docker virtual environment used to generate the images and data in this project are available at: XXX [author markup]

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