Calculate the Yield: Sorting Meat Science Facts from Fiction on Social Media

Rylie Lux, Channing Pieniazek, Dr. Laura Fischer, Dr. Courtney Meyers, Dr. Amber McCord; Texas Tech University

Introduction/Theoretical Framework

There are two ways false information is shared, misinformation and fake news. Misinformation is when an individual spreads information unintentionally (Bezbaruah et al., 2022; Khan et al, 2022). Fake news is the sharing of false information with the intent to mislead (Butler Horton, 2021). Although it has been around for a long time, the spreading of false information became an especially popular topic in 2020 during the COVID-19 pandemic, leading to what may be labeled as the "infodemic" (Gupta et al., 2022; Mendes Rocha et al., 2021; White et al., 2023, 2024). Social media has aided the spread of fake news as these catchy stories can be easily and quickly shared with peers (Mendes Rocha et al., 2021). While only a few studies in agricultural communications focus on fake news, it is a large issue in today's food market (Bezbaruah et al., 2022). Agriculture is a regular victim of misinformation (Butler Horton, 2021). Recently, there has been an increasing amount of blame placed on "contaminated meat" for athletes failing drug tests at major international competitions, including the 2024 Summer Olympics (Malatesta, 2024; Pells, 2024). The United States Anti-Doping Agency claims that "contaminated meat," or meat treated with anabolic steroids or other performance-enhancing drugs, can result in a positive test result in some cases for athletes (USADA, 2016). At the 2024 Paris Summer Olympics, Erriyon Knighton, an American track and field Olympian, tested positive for a banned drug, Trenbolone, a growth promotant commonly used in livestock operations to increase lean meat yield (Pells, 2024; Smith & Johnson, 2020). With fake news in agriculture being an understudied topic (Butler Horton, 2021), there is a need to identify what messages are being released regarding meat science in social media and which authors are speaking on this topic.

Conceptual Framework

To provide a greater understanding of how individuals acquire information and what information regarding meat residues is available, the study was informed by Information Manipulation Theory 2. In 1992, McCornack published the Information Manipulation Theory (IMT) stating deceptive messages are edited following a model of quantity, quality, relevance, and manner. The nuances involved with creating deceptive messages made this theory difficult to test in modern communication practices (Jacobs et al., 1996). However, IMT2 builds on the prior theory stating there are a variety of ways to deceive someone covertly (McCornack et al., 2014). IMT2 works to fill in the gaps from the initial theory and make it more fitting for use in research. The concepts of quality, quantity, relevance, and manner are used to describe regular human discourse as ways to deceive those around them, indicating when subjects should be wary of deception (McCornack et al., 2014).

Additionally, this study was also informed by the Credibility, Accuracy, Reasonableness, and Support (C.A.R.S.) Checklist created by Harris and Spinks (2007). Harris (2010) provided a strong foundation for online users to understand how they should evaluate and determine what sources to trust online. The C.A.R.S. Checklist (Harris and Spinks, 2007) lists four goals or questions that readers should answer when appraising a source: *Is the source created by someone*

educated and aware of the message quality? Is the source current and complete? Is the author telling the truth without bias? Could the reader easily confirm the information provided?

This study's foundation can be seen through the lens of three theories: *Intentional States, Cognitive Load,* and *Information Manipulation*. The emphasis on pattern detection between IMT2 and C.A.R.S. allowed us to build a checklist to follow during the coding process. In addition to IMT2, we utilized the Harris and Spinks (2007) framework and Zhou and Zafarani (2020) to evaluate online resources for credibility. By evaluating news sources across the fake news spectrum, the research team noted differences in the style, accuracy, support, and emotion of message structure and delivery.

Purpose and Objectives

The purpose of this study is to compare the impacts of credible and fake information shared online. To achieve this, the study followed four research objectives:

RO1: Determine the frequencies of messages across the Fake News Spectrum.
RO2: Describe Fake New Checklist variables through frequencies and percentages.
RO3: Compare author information variables across the Fake News Spectrum.
RO4: Compare content metric variables across the Fake News Spectrum.

Methods

This study is a content analysis of social media posts around meat science and meat residues using a Fake News Checklist to identify, describe, and compare fake and credible news patterns. Kerlinger (2000) defined content analysis as "studying and analyzing communication in a systematic, objective, and quantitative manner for the purpose of measuring variables" (p. 159). We created a 'Fake News Checklist' through established patterns of clues that fake news could be on consumers screens (Harris, 2010; Harris & Spinks, 2007; Khan et al., 2022; McCornack et al., 2014; Zhou et al., 2020; Zhou & Zafarani, 2020). This framework combines the research and instruction of prior works giving us a comprehensive guide to evaluating the news seen on social media. This checklist served as a yes/no questionnaire detailing patterns of credible and fake messages that would provide a quantifiable score for each message and place the messages in categories on a Fake News Spectrum.

All data used in this study was collected by Sprout Social from Twitter/X, Facebook, Instagram, YouTube, and Reddit between the dates of August 1 and 31, 2024. These dates were selected to cover notable events, including messages about anti-doping cases blaming contaminated meat from the 2024 Olympic games. A total of 4,763 messages were collected. A proportional stratified sample of 476 messages from this population was coded, after taking 10% of messages from each of the five platforms. To gather this 10% sample, the messages were divided into groups by platform, and every tenth message by postdate was selected for evaluation. This ensured that each platform's share of voice was preserved throughout the study. After culling irrelevant messages, a total of 343 messages were analyzed by the research team.

Sprout Social is a social media listening tool that allows users to evaluate a conversation on a topic across a variety of platforms. To build the Sprout Social listening board, researchers created a list of key words to serve as targets for the social monitoring software to find messages that contained those words. The keyword list was developed using prior literature in meat

science and agricultural communications research and observed conversations on social media (i.e., Kemper et al., 2023; Rana et al., 2019; Purslow & Zhang, 2022) and was reviewed by a panel of experts in the fields of agricultural communications, mass communications, and meat science. Some of these key words included in this study were: *Trenbolone, beta-agonists, growth promoters, food safety,* and *meat science*.

To conduct this content analysis, we evaluated previous literature, educational guides, and industry materials available to create the Fake News Checklist that includes hallmark traits of fake news messages found in the past on social media (Harris, 2010; Harris and Spinks, 2007; Khan et al., 2022; Zhou et al., 2020; Zhou & Zafarani, 2020). This checklist included 11 questions for readers to ask themselves when evaluating social media and news sources to be included in the score, as well as four other post and author characteristics collected by Sprout Social (i.e., author verification status and credential information, use of links or hashtags). These questions were asked to determine credibility*, unreliability,* and *accuracy.* In addition to these questions, verification status and author credentials were included in the evaluation of accuracy. Table 1 displays the variables that were determined using Sprout Social and the research team.

Table 1

Variables calculated by Sprout Social versus the Research Team

Sprout Social	Research Team
Author	Relevancy
Date Posted	Account Type
Number of Followers	Credentials
Message Type	Verified
Content Type	Platform
Post Engagement	Link Present
Sentiment	Hashtags Present
Message Type	Message Purpose
	General Topic

A codebook was created along with a checklist with detailed instructions for graduate student coders to evaluate posts for variables of interest. Intercoder reliability was established with a 15-message sample of the coded data. To analyze the data, we used descriptive statistics outlined by Field (2013) in SPSS 29. The descriptive statistics were analyzed using frequency counts and percentages, descriptive statistics, and crosstabulations.

Results/Findings

Descriptive data presented in these findings are a combination of data from the Sprout Social output and information evaluated during data analysis.

RO1: Determine the frequencies of messages across the Fake News Spectrum.

Through human coding, messages were assigned a place in the Fake News Spectrum based on earlier mentioned scoring criteria. *Credible* message scores ranged from 0 to 3. *Questionable* messages scored between 4 and 7. *Suspicious* messages scored between 8 and 10. *Fake* messages scored between 11 and 15. Table 2 displays the frequencies of these labels. *Questionable*

messages represented the largest portion (n = 220, 64.1%) of the messages evaluated; whereas, the fake messages represented the smallest portion of messages (n = 7, 2.0%).

Table 2

Frequency of Messages Across the Fake News Spectrum (N = 343)

Sector	Frequency	Frequency Percent
Credible	28	8.2
Questionable	220	64.1
Suspicious	88	25.7
Fake	7	2.0

RO2: Describe Checklist variables through frequencies and percentages.

There were 16 variables evaluated to establish each message's position in the Fake News Spectrum. These variables, evaluated mostly through presence or absence, either added one point or zero points to the final score. All *Credible* messages were delivered as complete thoughts and most (96.4%) messages shared the information objectively. Additionally, *Credible* messages shared up-to-date facts in their posts across all evaluated (n = 28, 100%). In contrast, all *Fake* messages did not share information objectively or mention outside sources in their copy. Additionally, *Credible* messages presented the least number of attributes from this portion of the checklist. None of the *Credible* messages used out-of-date facts, contained GSP errors, redundancies, swear words, or employed emotion in message delivery. One message (3.6%) used unexplained jargon in their message. On the other end of the spectrum, *Fake* messages did not present as uniform as *Credible* messages. All *Fake* messages (n = 7) contained GSP errors and were emotionally driven.

RO3: Compare author information variables across the Fake News Spectrum.

The analysis of *author information* variables across the Fake News Spectrum revealed distinct patterns based on account type, verification status, and credentials. Personal accounts accounted for 305 (88.9%) of the 343 messages in the sample, with all fake messages (n = 7) coming from personal accounts. However, along the Fake News Spectrum, messages from business accounts (n = 11; 39.3%) and non-profit accounts (n = 2; 7.1%) were deemed credible. In terms of *verification*, only 6 (1.7%) authors had verification badges, with 5 (83.3%) posting credible messages, and 1 (16.7%) posting a suspicious message. No verified authors posted fake messages. Regarding credentials, 322 (93.9%) authors had self-proclaimed (i.e., verification not from recognized entities such as universities, professional associations, or government), while 21 (6.1%) had institutional credentials (i.e., derived from universities, professional associations, etc.). All 7 fake messages were posted by authors with self-proclaimed credentials, and no fake messages came from authors with institutional credentials. Of the ten credentials available, authors without any credentials (288, 84.0%) were the majority.

RO4: Compare content information variables across the Fake News Spectrum.

Sprout collected engagement metrics across all five platforms for our message sample. These included comments, likes, and shares, which are common interactions on the selected platforms. The message sample collected 13,044 total engagements, with a majority (n = 10,113, 77.5%) of those coming from credible messages. Each sector of the Fake News Spectrum had a minimum of zero engagements with maximum amounts ranging from 4 to 8,080. Evaluation of which

topics are more often associated with fake news is important as marketing practitioners should be prepared for such issues to arise. *Meat Processing and Food Safety* overall was a popular topic of discussion (*n* = 102, 29.7%) across the entire Fake News Spectrum. Most credible (*n* = 10, 35.7%), questionable (*n* = 64, 29%), and suspicious (*n* = 27, 30.7%) messages explored this topic as well. The most discussed topic by fake messages was *Food and Health* (*n* = 4, 57.1%).

Conclusion/Recommendations/Implications

Fake news is not a new issue for the agricultural industry (Bezbaruah et al., 2022; Butler Horton, 2021; Edgar et al., 2017). However, an "infodemic" has cast a shadow over raising livestock and food production. In this study, we found the majority of the messages collected did not venture into true fake news, as only seven messages were labeled as *Fake* out of 343 evaluated. However, the largest portion (*n* = 220, 64.1%) of messages fell into the *Questionable* sector of the Fake News Spectrum, allowing us to presume that it is hard for users to determine what is real and fake on social media, confirming findings of prior literature. It is hard to research motives on social media without communicating directly with the authors of these posts. The concept of deceptive communication has been mentioned in fake news literature (Zhou et al., 2020). Knowing if online authors were sharing fake news intentionally or not was not a variable evaluated in this study but could be an interesting focus for future studies. Social media users should still have ample opportunity to find sources they trust inside and outside their biases. We should encourage individual users and companies to include their education, goals, and other credentials in their bios or account descriptions when discussing topics across meat science. Confirming information found online with credentialed authors will help build trust between consumers and meat scientists.

Noticing patterns is key in determining if a message is telling the truth or trying to trick its readers (Allcott & Gentzkow, 2017; Jacobs, 2024; Konopliov, 2024). Prior studies have evaluated college students' ability to detect such false messages (Butler Horton, 2021), but future research could build on these and test the impact of a checklist similar to what is used in our study. Additionally, a focus should be placed on media and agricultural literacy when combatting the spread of fake news. Increasing accessibility to media literacy materials will help consumers begin to see the differences between credible, questionable, suspicious, and fake messages (Barthel et al., 2016; Kirshenbaum, 2022). Keeping in mind those three theories used to build the conceptual framework it is important to look for ways to implement practices to reduce some of these phenomena for the public. Communicators should be intentional with their messages as well as report these messages in a way that reduces the cognitive load for the audience. Finally, it is vital to keep in mind how information can be manipulated.

Transparency is trending as a demand from consumers for their grocery products. Sticking to tradition and "that's just the way we do things" will not satisfy that demand anymore. In order to gain the trust of consumers, they need to feel safe and understand the processes their food goes through to get onto their plates. Providing up to date information and examples on social media in easy to consume packages like photo and short-form video posts is one solution agricultural companies should use. Social media users should still have ample opportunity to find sources they trust inside and outside their biases. We should encourage individual users and companies to include their education, goals, and other credentials in their bios or account descriptions when discussing topics across meat science. Confirming information found online with credentialed authors will help build trust between consumers and meat scientists.

References

Allcott, H., & Gentzkow, M. (2017). Social media and fake news in the 2016 election. *Journal of Economic Perspectives*, *31*(2), 211–236. https://doi.org/10.1257/jep.31.2.211

Barthel, M., Mitchell, A., & Holcomb, J. (2016). *Many Americans believe fake news is sowing confusion* (Vol. 15). www.pewresearch.org.

Bezbaruah, S., Dhir, A., Talwar, S., Tan, T. M., & Kaur, P. (2022). Believing and acting on fake news related to natural food: the influential role of brand trust and system trust. *British Food Journal*, *124*(9), 2937–2962. https://doi.org/10.1108/BFJ-02-2021-0190

Butler Horton, M. K. (2021). *College Students' Perceived Ability Versus Actual Ability to Identify Fake News on Agricultural Topics*. Texas Tech University.

Edgar, L. D., Johnson, D. M., & Estes, S. (2017). Poultry production messaging in two national-circulation newspapers. *Journal of Applied Communications*, *101*(1). https://doi.org/10.4148/1051-0834.1010

Field, A. (2013). *Discovering Statistics Using IBM SPSS Statistics: North American Edition* (5th ed.). Sage Publications Ltd.

Gupta, A., Li, H., Farnoush, A., & Jiang, W. (2022). Understanding patterns of COVID infodemic: A systematic and pragmatic approach to curb fake news. *Journal of Business Research*, *140*, 670–683. https://doi.org/10.1016/j.jbusres.2021.11.032

Harris, R. (2010). *Evaluating Internet Research Sources*.

Harris, R., & Spinks, A. (2007). *The C.A.R.S. checklist for evaluating internet sources*.

Jacobs, J. (2024). Spotting Fake News. *Texas Tech University Library*. https://guides.library.ttu.edu/spottingfakenews

Jacobs, S., Dawson, E. J., & Brashers, D. (1996). Information manipulation theory: A replication and assessment. *Communication Monographs*, *63*(1), 70–82. https://doi.org/10.1080/03637759609376375

Kemper, J. A., Benson-Rea, M., Young, J., & Seifert, M. (2023). Cutting down or eating up: Examining meat consumption, reduction, and sustainable food beliefs, attitudes, and behaviors. *Food Quality and Preference*, *104*. https://doi.org/10.1016/j.foodqual.2022.104718

Kerlinger, F. N. (2000). *Foundations of behavioral research* (4th ed.). Harcourt College Publishers.

Khan, A., Brohman, K., & Addas, S. (2022). The anatomy of 'fake news': Studying false messages as digital objects. *Journal of Information Technology*, *37*(2), 122–143. https://doi.org/10.1177/02683962211037693

Kirshenbaum, S. (2022). *New MSU Survey Reveals Growing Distrust of Food Experts and Widespread Concern Over Food Prices*.

Konopliov, A. (2024, June 26). *Key statistics on fake news & misinformation in media in 2024*. Redline. https://redline.digital/fake-news-statistics/

Malatesta, P. (2024). *World Anti-Doping Agency investigates food contamination doping claims*. KPCW - NPR. https://www.kpcw.org/sports/2024-07-31/world-anti-doping-agency-investigates-food-contamination-doping-claims

McCornack, S. A. (1992). Information manipulation theory. *Communication Monographs*, *59*(1), 1–16. https://doi.org/10.1080/03637759209376245

McCornack, S. A., Morrison, K., Paik, J. E., Wisner, A. M., & Zhu, X. (2014). Information manipulation theory 2: A propositional theory of deceptive discourse production. *Journal of Language and Social Psychology*, *33*(4), 348–377. https://doi.org/10.1177/0261927X14534656

Mendes Rocha, Y., Acácio De Moura, G., Desidério, G. A., Henrique De Oliveira, C., Dantas Lourenço, F., Deadame, L., & Nicolete, F. (2021). The impact of fake news on social media and its influence on health during the COVID-19 pandemic: a systematic review. *Journal of Public Health: From Theory to Practice*, *31*, 1007–1016. https://doi.org/10.1007/s10389-021-01658-z/Published

Pells, E. (2024). *Attorney calls Olympic sprinter Erriyon Knighton 'collateral damage' in widening anti-doping feud*. AP. https://apnews.com/article/olympics-knighton-doping-contamination-d99bc38e44332fb1933fbeadf406d5a6

Purslow, P. P., & Zhang, W. (2022). Introduction to the special issue of meat science on 'perspectives on consumer attitudes to meat consumption.' *Meat Science*, *193*. https://doi.org/10.1016/j.meatsci.2022.108956

Rana, M. S., Lee, S. Y., Kang, H. J., & Hur, S. J. (2019). Reducing veterinary drug residues in animal products: A review. *Food Science of Animal Resources*, *39*(5), 687–703. https://doi.org/10.5851/kosfa.2019.e65

Smith, Z. K., & Johnson, B. J. (2020). Mechanisms of steroidal implants to improve beef cattle growth: a review. *Journal of Applied Animal Research, 48*(1), 133-141. https://doi.org/10.1080/09712119.2020.1751642

USADA. (2016). *Clenbuterol and Meat Contamination*. AthleteConnect. https://www.usada.org/spirit-of-sport/clenbuterol-and-meat-contamination/

White, B. K., Burns, S. K., Carson, J., & Scott, J. A. (2024). Mapping breastfeeding and COVID-19 related content and engagement on Facebook: Results from an online social listening study. *Health Promotion Journal of Australia*, *35*(1), 242–250. https://doi.org/10.1002/hpja.729

White, B. K., Gombert, A., Nguyen, T., Yau, B., Ishizumi, A., Kirchner, L., León, A., Wilson, H., Jaramillo-Gutierrez, G., Cerquides, J., D'Agostino, M., Salvi, C., Sreenath, R. S., Rambaud, K., Samhouri, D., Briand, S., & Purnat, T. D. (2023). Using Machine Learning Technology to Enhance Digital Social Understanding for the COVID-19 Infodemic: Development and implementation of the Early AI-Supported Response with Social Listening (EARS) platform. *JMIR Infodemiology*, *3*. https://doi.org/10.2196/47317

Zhou, X., Jain, A., Phoha, V. V., & Zafarani, R. (2020). Fake News Early Detection: A Theory-driven Model. *Digital Threats: Research and Practice*, *1*(2). https://doi.org/10.1145/3377478

Zhou, X., & Zafarani, R. (2020). A Survey of Fake News: Fundamental Theories, Detection Methods, and Opportunities. *ACM Computing Surveys*, *53*(5). https://doi.org/10.1145/3395046