with the observation that in many cases survey respondents made mention of personal opinions and assumptions — but not empirical details — having influenced their decisions. This suggests that an individual's already-existing information-and influence-networks have a substantive impact on what they ”see” and ”understand” in the survey items. We contrast this with the accuracy of survey responses accomplished when the second author (himself a credentialed social scientist) completed the same survey using codes produced by our undergraduate social science research assistants to guide responses to the survey items. Definitions of these codes in our code dictionary indicated that these codes accounted for objective features of survey items (e.g., terminology, match or mismatch of images and text, source citations, etc.), and analytic social science interpretations of combinations of these factors within particular survey items. The accuracy of real/fake determinations was 68% correct in this application.

To provide more detail on this process, codes like ”Questionable formatting,” ”Questionable language,” and ”Clickbait” were used to identify features such as use of text colors, bold and italic fonts, and hyperbolic terminology *in patterns* that — when made apparent — led the reader's focus to politically-charged interpretations mostly uncommon in truthful items. Similarly, disagreement between titles, pictures, and story contents suggests editorial intent in attracting individuals with preconceived ideas about the item. It was the *lack of* use of such codes which often cleared the way toward an interpretation that an item was more likely to be factual. This suggests that fake items are those which demonstrate particular patterns in the use of formatting, vocabulary, and semantic interpretations produced through semantic analysis of those objectively-identifiable patterns. While 68% accuracy is hardly a demonstration of remarkable success, it does reflect a substantive improvement in accuracy achieved when using more rigorous social science logic. This reinforces existing research indicating that (a) when left to their own ”gut-hunch” means, humans are poor at identifying fake news [1], [4]. It also points to (b) the relative value of replacing ”gut-hunch” processing with analytic social science (i.e., focusing on abstractions based on empirically identifiable factors, patterns of those factors, and semantic analysis of those patterns found in news media) as a more promising approach for discriminating real and fake news items.

From this, and with the goal of improving humans' ability to discriminate fake from real news, we suggest two things. First, we advise development of instruction and tools that augment people with information, skills, and tools supporting an empirically-grounded approach to assessment of news. Second, we advise development and systematic delivery of instruction that demonstrates hazards of a non-empirical (or “gut-hunch”) approach to assessment of news. In combination, these will aid people in assessing news items, and raise more awareness of the problem in order to decrease the unconscious spread of misinformation [14]–[16].

In addition, this pilot study highlights several things that must be more deliberately pursued in future work. First, creation of a taxonomy of empirically identifiable factors in news sources. Second, determine individual and combined predictive power those factors have in detecting fake news. Third, identify the direction (real/fake) and strength of influence of factors that lead individuals to make ”gut-hunch” judgments about news items. Fourth and finally, identify the reliability of readers'/viewers' non-empirically-grounded judgements about news items. Accomplishing these four things will provide firm ground for taking next steps in improving means for supporting people in detecting real or fake news and developing behavioral models of human credibility assessment. The latter will contribute to a better understanding of misinformation spread in social networks.

Acknowledgements: We would like to thank Alyse Palsulich (Treasure Valley Math and Science Center High School) for contributing to initial stages of this research, and Allyssa Hernandez and Ramona Hinrichs (Sociology department, Boise State University) for helping with the inductive coding process. The first author has been partially supported by the National Science Foundation under Award no. 1943370.

REFERENCES

[1] S. Kumar and N. Shah, “False information on web and social media: A survey,” *CoRR*, vol. abs/1804.08559, 2018.

[2] S. Wineburg, S. McGrew, J. Breakstone, and T. Ortega, “Evaluating information: The cornerstone of civic online reasoning,” *Stanford Digital Repository. Retrieved January*, vol. 8, p. 2018, 2016.

[3] M. Gabielkov, A. Ramachandran, A. Chaintreau, and A. Legout, “Social clicks: What and who gets read on twitter?” *ACM SIGMETRICS Performance Evaluation Review*, vol. 44, no. 1, pp. 179–192, 2016.

[4] S. Vosoughi, D. Roy, and S. Aral, “The spread of true and false news online,” *Science*, vol. 359, no. 6380, pp. 1146–1151, 2018.

[5] M. J. Metzger and A. J. Flanagin, “Psychological approaches to credibility assessment online,” *The handbook of the psychology of communication technology*, vol. 32, pp. 445–466, 2015.

[6] M. J. Metzger, “Making sense of credibility on the web: Models for evaluating online information and recommendations for future research,” *Journal of the American Society for Information Science and Technology*, vol. 58, no. 13, pp. 2078–2091, 2007.

[7] X. Zhou and R. Zafarani, “A survey of fake news: Fundamental theories, detection methods, and opportunities,” *ACM Comput. Surv.*, vol. 53, no. 5, 2020.

[8] B. D. Horne, D. Nevo, J. O'Donovan, J. Cho, and S. Adali, “Rating reliability and bias in news articles: Does AI assistance help everyone?” in *ICWSM*, 2019, pp. 247–256.

[9] F. Jin, E. Dougherty, P. Saraf, Y. Cao, and N. Ramakrishnan, “Epidemiological modeling of news and rumors on twitter,” in *Proceedings of the 7th Workshop on Social Network Mining and Analysis*, 2013, p. 8.

[10] J.-H. Cho, S. Rager, J. O'Donovan, S. Adali, and B. D. Horne, “Uncertainty-based false information propagation in social networks,” *ACM Transactions on Social Computing*, vol. 2, no. 2, p. 5, 2019.

[11] K. Shu, S. Wang, and H. Liu, “Beyond news contents: The role of social context for fake news detection,” in *WSDM*. ACM, 2019, pp. 312–320.

[12] J. Saldaña, *The coding manual for qualitative researchers*. Sage, 2015.

[13] M. LeCompte and J. J. Schensul, “Analysis from the bottom up: the item level of analysis,” *Analyzing and Interpreting Ethnographic Data*, pp. 67–83, 1999.

[14] P. America. (2018) Faking news: Fraudulent news and the fight for truth. [Online]. Available: https://pen.org/faking-news/

[15] J. Kahne and B. Bowyer, “Educating for democracy in a partisan age: Confronting the challenges of motivated reasoning and misinformation,” *American Educational Research Journal*, vol. 54, no. 1, pp. 3–34, 2017.

[16] S. Van der Linden, A. Leiserowitz, S. Rosenthal, and E. Maibach, “Inoculating the public against misinformation about climate change,” *Global Challenges*, vol. 1, no. 2, p. 1600008, 2017.