COM 903 • Advanced Research Methods in Communication

Fall 2024 | Section 001 | Mon, 12:40-3:30pm

Instructor: Jacob T. Fisher, Ph.D. **E-mail:** jtf@msu.edu	**Office Hours** Mondays, 3:30-5pm

Course Description:

This graduate-level course serves as an introduction to advanced methods for the study of communication. The course focuses on three core areas: computational methods and big data, bio- and psycho-physiological methods, and emerging applications of artificial intelligence, including transformers and large language models (LLMs). Students will explore how new forms of data and new analytical techniques are reshaping communication research. By the end of this course, students will have a comprehensive understanding of these cutting-edge methodologies and their implications for the study of communication and adjacent social scientific domains.

Objectives

Upon completion of this course, students should be able to accomplish the following objectives:

1. Understand and critically evaluate advanced research methods in communication, including computational approaches, big data analytics, bio- and psycho-physiological techniques, and AI-based methodologies, articulating their foundations, applications, strengths, and limitations.
2. Apply knowledge of these methods to design studies that address complex communication phenomena, demonstrating the ability to integrate multiple approaches and consider ethical, pragmatic, and other implications.
3. Analyze and interpret data generated from these advanced research methods, drawing conclusions about communication processes and effectively communicating these conclusions and their implications for communication theory and practice.

This class will combine lectures, readings, hands-on data analysis exercises, and group discussions. Students are expected to engage deeply with course materials, completing all assigned readings and video content prior to class sessions. These materials will serve as the foundation for in-class activities, discussions, and practical applications of the methods covered.

Digital Tools:

D2L - We will be using D2L to manage all assignments, reading materials, and quizzes. If you have not yet logged into D2L, you can do so at d2l.msu.edu. Note that this is one of the first semesters that I will be using D2L, so it's possible that there may be some bumps along the way. I appreciate your patience. Please reach out if you have questions or if something is confusing or seems missing.

Sample Readings [*]

Module 1: Computational Methods

Baden, C., Pipal, C., Schoonvelde, M., & van der Velden, M. A. C. G. (2021). Three gaps in computational text analysis methods for social sciences: A research agenda. *Communication Methods and Measures*, 1–18.

Berger, J., & Packard, G. (2022). Using natural language processing to understand people and culture. *The American Psychologist*, *77*(4).

boyd, D. & Crawford, K. (2012). Critical questions for big data. Information, Communication & Society,15, 662-679.

Castro, N., & Siew, C. S. Q. (2020). Contributions of modern network science to the cognitive sciences: Revisiting research spirals of representation and process. *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences*, *476*(2238), 20190825.

Chetty, R., Jackson, M. O., Kuchler, T., Stroebel, J., Hendren, N., Fluegge, R. B., Gong, S., Gonzalez, F., Grondin, A., Jacob, M., Johnston, D., Koenen, M., LagunaMuggenburg, E., Mudekereza, F., Rutter, T., Thor, N., Townsend, W., Zhang, R., Bailey, M., Barberá, P., Bhole, M, & Wernerfelt, N. (2022). Social capital I: Measurement and associations with economic mobility. Nature, 1–14.

Chetty, R., Jackson, M. O., Kuchler, T., Stroebel, J., Hendren, N., Fluegge, R. B., Gong, S., Gonzalez, F., Grondin, A., Jacob, M., Johnston, D., Koenen, M., Laguna-Muggenburg, E., Mudekereza, F., Rutter, T., Thor, N., Townsend, W., Zhang, R., Bailey, M., Barberá, P., Bhole, M, Wernerfelt, N. (2022). Social capital II: Determinants of economic connectedness. Nature, 1–13.

Christner, C., Urman, A., Adam, S., & Maier, M. (2022). Automated Tracking Approaches for Studying Online Media Use: A Critical Review and Recommendations. *Communication Methods and Measures*, *16*(2), 79–95.

Clemm von Hohenberg, B., Stier, S., Cardenal, A. S., Guess, A. M., Menchen-Trevino, E., & Wojcieszak, M. (2024). Analysis of web browsing data: A guide. *Social Science Computer Review*, 08944393241227868.

Dubova, M., & Goldstone, R. L. (2023). Carving joints into nature: Reengineering scientific concepts in light of concept-laden evidence. *Trends in Cognitive Sciences*, *27*(7), 656–670.

Dyer, E. L., & Kording, K. (2023). Why the simplest explanation isn't always the best. *Proceedings of the National Academy of Sciences*, *120*(52), e2319169120.

Golder, S. A., & Macy, M. W. (2014). Digital footprints: Opportunities and challenges for online social research. Annual Review of Sociology, 40, 129-152.

[*] *Note that this is an initial list of readings, and as such it is subject to change.*

Grimmer, J., & Stewart, B. M. (2013). Text as data: The promise and pitfalls of automatic content analysis methods for political texts. Political Analysis, 21(3), 267–297.

Grimmer, J., Roberts., M. E., & Stewart, B. M. (2021). Machine learning for social science: An agnostic approach. Annual Review of Political Science, 24, 1-25.

Hofman, J. M., Watts, D. J., Athey, S., Garip, F., Griffiths, T. L., Kleinberg, J., . . .Yarkoni, T. (2021). Integrating explanation and prediction in computational social science. Nature, 595(7866), 181-188.

Lazer, D., Pentland, A. S., Adamic, L., Aral, S., Barabasi, A. L., Brewer, D., ... & Jebara, T. (2009). Life in the network: The coming age of computational social science. Science, 323, 721-723.

Lazer, D. M. J., Pentland, A., Watts, D. J., Aral, S., Athey, S., Contractor, N., Freelon, D., Gonzalez-Bailon, S., King, G., Margetts, H., Nelson, A., Salganik, M. J., Strohmaier, M., Vespignani, A., & Wagner, C. (2020). Computational social science: Obstacles and opportunities. Science, 369(6507), 1060.

Lazer, D., Hargittai, E., Freelon, D., Gonzalez-Bailon, S., Munger, K., Ognyanova, K., & Radford, J. (2021). Meaningful measures of human society in the twenty-first century. Nature, 595(7866), 189-196.

Lin, J. (2015). On building better mousetraps and understanding the human condition: Reflections on big data in the social sciences. The Annals of the American Academy of Political and Social Science, 659(1), 33–47.

Lones, M. A. (2021). How to avoid machine learning pitfalls: A guide for academic researchers. https://arxiv.org/pdf/2108.02497.pdf.

Lukito, J., Greenfield, J., Yang, Y., Dahlke, R., Brown, M. A., Lewis, R., & Chen, B. (2024). Audio-as-Data Tools: Replicating Computational Data Processing. *Media and Communication*, *12*(0).

Molina, M., & Garip, F. (2019). Machine learning for sociology. Annual Review of Sociology, 45, 27-45.

Ohme, J., Araujo, T., Boeschoten, L., Freelon, D., Ram, N., Reeves, B. B., & Robinson, T. N. (2023). Digital trace data collection for social media effects research: APIs, data donation, and (screen) tracking. *Communication Methods and Measures*, *0*(0), 1–18.

Onnela, J. P., Saramäki, J., Hyvönen, J., Szabó, G., Lazer, D., Kaski, K., ... & Barabási, A. L. (2007). Structure and tie strengths in mobile communication networks. Proceedings of the National Academy of Sciences, 104, 7332-7336.

Salganik, M. J. (2018). Bit by bit: Social research in the digital age. Princeton, NJ: Princeton University Press.

Toubia, O., Berger, J., & Eliashberg, J. (2021). How quantifying the shape of stories predicts their success. Proceedings of the National Academy of Sciences, 118(26), e2011695118.

van Atteveldt, W. & Peng, T. Q. (2018). When communication meets computation: Opportunities, challenges, and pitfalls in computational communication science. Communication Methods and Measures, 12, 81-92.

Wagner, C., Strohmaier, M., Olteanu, A., Kıcıman, E., Contractor, N., & Eliassi-Rad, T. (2021). Measuring algorithmically infused societies. Nature, 595(7866), 197-204.

Watts, D. J. (2004). The “new” science of networks. Annual Review of Sociology, 30, 243-270.

Watts, D. J. (2017). Should social science be more solution-oriented? Nature Human Behaviour, 1, 0015

Yu, B., & Kumbier, K. (2020). Veridical data science. *Proceedings of the National Academy of Sciences*, *117*(8), 3920–3929.

Module 2: Bio- and Psychophysiological Approaches

Cappella, J. N. (1996). Why biological explanation? Journal of Communication, 46(3), 4–7.

Cohen, M. X. (2017). Where does EEG come from and what does it mean? *Trends in Neurosciences*, *40*(4), 208–218.

Cushman, F. (2024). Computational social psychology. *Annual Review of Psychology*, *75*(1), 625–652.

Eickhoff, S. B., Milham, M., & Vanderwal, T. (2020). Towards clinical applications of movie fMRI. *NeuroImage*, 116860.

Egner, T. (2023). Principles of cognitive control over task focus and task switching. *Nature Reviews Psychology*, *2*(11).

Falk, E. B. (2012). Can neuroscience advance our understanding of core questions in Communication Studies? An overview of Communication Neuroscience. In S. Jones (Ed.), *Communication @ The Center*. Hampton Press.

Fisher, J. T., & Hamilton, K. (2021). Integrating media selection and media effects using decision theory. *Journal of Media Psychology*, 33(4), 215–225.

Fisher, J. T., Hopp, F. R., & Weber, R. (2023). Cognitive and perceptual load have opposing effects on brain network efficiency and behavioral variability in ADHD. *Network Neuroscience*, 1–42.

Fisher, J. T., Huskey, R., Keene, J. R., & Weber, R. (2018). The limited capacity model of motivated mediated message processing: Looking to the future. *Annals of the International Communication Association*, *42*(4), 291–315.

Fisher, J. T., Keene, J. R., Huskey, R., & Weber, R. (2018). The limited capacity model of motivated mediated message processing: Taking stock of the past. *Annals of the International Communication Association*, *42*(4), 270–290.

Finn, E. S., Glerean, E., Khojandi, A. Y., Nielson, D., Molfese, P. J., Handwerker, D. A., & Bandettini, P. (2019). Idiosynchrony: From shared responses to individual differences during naturalistic neuroimaging. *NeuroImage*, 215(116828).

Finn, E. S., Poldrack, R. A., & Shine, J. M. (2023). Functional neuroimaging as a catalyst for integrated neuroscience. *Nature*, *623*(7986).

Frömer, R., & Shenhav, A. (2022). Filling the gaps: Cognitive control as a critical lens for understanding mechanisms of value-based decision-making. *Neuroscience & Biobehavioral Reviews*, *134*, 104483.

Genon, S., Reid, A., Langner, R., Amunts, K., & Eickhoff, S. B. (2018). How to characterize the function of a brain region. *Trends in Cognitive Sciences*, *22*(4), 350–364.

Gong, X., & Huskey, R. (2023). Moving behavioral experimentation online: A tutorial and some recommendations for drift diffusion modeling. *American Behavioral Scientist*, 00027642231207073.

Gong, X., Huskey, R., Eden, A., & Ulusoy, E. (2023). Computationally modeling mood management theory: A drift-diffusion model of people's preferential choice for valence and arousal in media. *Journal of Communication*, *73*(5), 476–493.

Hasson, U., Landesman, O., Knappmeyer, B., Vallines, I., Rubin, N., & Heeger, D. J. (2008). Neurocinematics: The neuroscience of film. *Projections*, 2(1), 1–26.

Hopp, F. R., Amir, O., Fisher, J. T., Grafton, S., Sinnott-Armstrong, W., & Weber, R. (2023). Moral foundations elicit shared and dissociable cortical activation modulated by political ideology. *Nature Human Behaviour*, 1–17.

Huskey, R., Bue, A. C., Eden, A., Grall, C., Meshi, D., Prena, K., Schmälzle, R., Scholz, C., Turner, B. O., & Wilcox, S. (2020). Marr's tri-level framework integrates biological explanation across communication subfields. *Journal of Communication*, 70(3), 356–378.

Huskey, R., Keene, J. R., Wilcox, S., Gong, X., Adams, R., & Najera, C. J. (2022). Flexible and modular brain network dynamics characterize flow experiences during media use: A functional magnetic resonance imaging study. *Journal of Communication*, *72*(1), 6–32.

Mathôt, S. (2018). Pupillometry: psychology, physiology, and function. *Journal of Cognition*, *1*(1), 16.

Myers, C. E., Interian, A., & Moustafa, A. A. (2022). A practical introduction to using the drift diffusion model of decision-making in cognitive psychology, neuroscience, and health sciences. *Frontiers in Psychology*, *13*.

Quesque, F., Apperly, I., Baillargeon, R., Baron-Cohen, S., Becchio, C., Bekkering, H., Bernstein, D., Bertoux, M., Bird, G., Bukowski, H., Burgmer, P., Carruthers, P., Catmur, C., Dziobek, I., Epley, N., Erle, T. M., Frith, C., Frith, U., Galang, C. M., … Brass, M. (2024). Defining key concepts for mental state attribution. *Communications Psychology*, *2*(1), 1–5.

Tamir, D. I., & Thornton, M. A. (2023). Predicting other people shapes the social mind. In *Advances in Experimental Social Psychology*. Academic Press.

van Bree, S. (2023). A critical perspective on neural mechanisms in cognitive neuroscience: Towards unification. *Perspectives on Psychological Science*, 17456916231191744.

Varoquaux, G., Schwartz, Y., Poldrack, R. A., Gauthier, B., Bzdok, D., Poline, J.-B., & Thirion, B. (2018). Atlases of cognition with large-scale human brain mapping. *PLOS Computational Biology*, *14*(11), e1006565.

Weber, R., Mathiak, K., & Sherry, J. L. (2008). The neurophysiological perspective in mass communication research. In M. Beatty, J. McCroskey, & K. Floyd (Eds.), *Biological dimensions of communication: Perspectives, methods, and research* (pp. 43–73). Hampton Press.

Weber, R., Eden, A., Huskey, R., Mangus, J. M., & Falk, E. (2015). Bridging media psychology and cognitive neuroscience: Challenges and opportunities. *Journal of Media Psychology*, 27(3), 146–156.

Wheatley, T., Thornton, M. A., Stolk, A., & Chang, L. J. (2023). The emerging science of interacting minds. *Perspectives on Psychological Science*, 17456916231200177.

Zgonnikov A., Aleni A., Piiroinen P. T., O'Hora D., & di Bernardo M. (2017). Decision landscapes: Visualizing mouse-tracking data. *Royal Society Open Science*, *4*(11), 170482.

Module 3: Transformers, Deep Learning, & Artificial Intelligence

Buttrick, N. (2024). Studying large language models as compression algorithms for human culture. *Trends in Cognitive Sciences*, *28*(3), 187–189.

Demszky, D., Yang, D., Yeager, D. S., Bryan, C. J., Clapper, M., Chandhok, S., Eichstaedt, J. C., Hecht, C., Jamieson, J., Johnson, M., Jones, M., Krettek-Cobb, D., Lai, L., Jones-Mitchell, N., Ong, D. C., Dweck, C. S., Gross, J. J., & Pennebaker, J. W. (2023). Using large language models in psychology. *Nature Reviews Psychology*, *2*(11), 688–701.

de Santana Correia, A., & Colombini, E. L. (2022). Attention, please! A survey of neural attention models in deep learning. *Artif. Intell. Rev.*, *55*(8), 6037–6124.

Frank, M. C. (2023). Baby steps in evaluating the capacities of large language models. *Nature Reviews Psychology*, *2*(8), 451–452.

Heseltine, M., & Clemm von Hohenberg, B. (2024). Large language models as a substitute for human experts in annotating political text. *Research & Politics*, *11*(1), 20531680241236239.

Jackson, J. C., Watts, J., List, J.-M., Puryear, C., Drabble, R., & Lindquist, K. A. (2022). From text to thought: How analyzing language can advance psychological science. *Perspectives on Psychological Science*, *17*(3), 805–826.

Ji, E. Y. (2024). Large Language Models: A Historical and Sociocultural Perspective. *Cognitive Science*, *48*(3), e13430

Kjell, O. N. E., Kjell, K., & Schwartz, H. A. (2024). Beyond rating scales: With targeted evaluation, large language models are poised for psychological assessment. *Psychiatry Research*, *333*, 115667.

Malik, M., Youk, S., & Weber, R. (2024). Beyond the screen: Exploring moral understanding via user comments on YouTube short films. *Journal of Media Psychology*, *36*(4), 231–243.

Markowitz, D. M. (2021). The Meaning Extraction Method: An Approach to Evaluate Content Patterns From Large-Scale Language Data. *Frontiers in Communication*, *6*.

Markowitz, D. M. (2024). Can generative AI infer thinking style from language? Evaluating the utility of AI as a psychological text analysis tool. *Behavior Research Methods*, *56*(4), 3548–3559.

Markowitz, D. M., & Hancock, J. T. (2024). Generative AI Are More Truth-Biased Than Humans: A Replication and Extension of Core Truth-Default Theory Principles. *Journal of Language and Social Psychology*, *43*(2), 261–267

Messeri, L., & Crockett, M. J. (2024). Artificial intelligence and illusions of understanding in scientific research. *Nature*, *627*(8002), 49–58.

Ornstein, J. T., Blasingame, E. N., & Truscott, J. S. (2023). *How to train your stochastic parrot: Large language models for political texts*.

Raiaan, M. A. K., Mukta, Md. S. H., Fatema, K., Fahad, N. M., Sakib, S., Mim, M. M. J., Ahmad, J., Ali, M. E., & Azam, S. (2024). A Review on Large Language Models: Architectures, Applications, Taxonomies, Open Issues and Challenges. *IEEE Access*, *12*, 26839–26874. IEEE Access.

Schrimpf, M., Blank, I., Tuckute, G., Kauf, C., Hosseini, E. A., Kanwisher, N., Tenenbaum, J., & Fedorenko, E. (2021). *The neural architecture of language: Integrative modeling converges on predictive processing* (p. 2020.06.26.174482). bioRxiv.

Sievers, B., & Thornton, M. A. (2024). Deep social neuroscience: The promise and peril of using artificial neural networks to study the social brain. *Social Cognitive and Affective Neuroscience*, *19*(1), nsae014.

Urban, C. J., & Gates, K. M. (2021). Deep learning: A primer for psychologists. *Psychological Methods*, *26*(6).

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł., & Polosukhin, I. (2017). Attention is all you need. *Advances in Neural Information Processing Systems*, *30*.

Ziems, C., Held, W., Shaikh, O., Chen, J., Zhang, Z., & Yang, D. (2024). Can Large Language Models Transform Computational Social Science? *Computational Linguistics*, *50*(1), 237–291.