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Coordination: Theoretical, Methodological, and Experimental Perspectives

Author
Paxton, Alexandra

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Coordination: Theoretical, Methodological, and Experimental Perspectives

A dissertation submitted in partial satisfaction of the requirements for the degree Doctor of Philosophy

in

Cognitive and Information Sciences

by

Alexandra Erin Paxton

Committee in charge:

Professor Rick Dale, Chair
Professor Teenie Matlock
Professor Jeff Yoshimi

2015

The dissertation of Alexandra Erin Paxton is approved, and it is acceptable

in quality and form for publication on microfilm and electronically:

Professor Rick Dale, Chair

Professor Teenie Matlock

Professor Jeffrey Yoshimi

University of California, Merced

2015

This dissertation is dedicated to the family and friends
whose constant love and support got me through this with my sanity:

to my incredible husband, Dale Paxton,
who has been a better partner on this road
than I could have ever imagined;

to my friends,
who offered encouragement, perspective,
open tables, and amazing company;

and to my family,
who sparked a lifelong passion for knowledge
and cheered me on even from half a world away.

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Thanks to Teenie Matlock for reminding me to keep an eye toward the deeper meaning of language and for inspiring in me a dedication to cultivate a diverse but unified community wherever I am. Thanks to Jeff Yoshimi for pushing me to consider the broader implications of my work and for giving me a profound appreciation for philosophy's role in cognitive science. Thanks to both of you for your honesty, positivity, and advice, both as committee members and mentors.

I'd also like to thank all of the other members (past and present) of the UC Merced Cognitive and Information Sciences group who have helped create a truly outstanding intellectual community. From undergraduate research assistants to graduate students to faculty members, this community challenges its members to grow and supports us as we do. It has been a joy to be part of it.

Finally, I would like to thank the University of California, Merced and its Cognitive and Information Sciences group for their support—including generous financial support—over the course of my graduate career here. I would also like to thank the UC Merced Graduate Division for financial support through the Graduate Dean's Dissertation Fellowship (AY 2015-2016).

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The text of Chapter 2 of this dissertation will be submitted for publication with co-author Rick Dale. The text of Chapter 3 is a reprint (with permission of Springer) of the article "PsyGlass: Capitalizing on Google Glass for Naturalistic Data Collection" as it appeared in *Behavior Research Methods*, which was co-authored by Kevin Rodriguez and Rick Dale. The text of Chapter 4 will be submitted for publication with co-authors Rick Dale and Daniel C. Richardson.

Curriculum Vita

Alexandra E. Paxton

(Née Loan)

paxton.alexandra@gmail.com
http://www.alexandrapaxton.com

Education

2011–2015	PhD in Cognitive and Information Sciences University of California, Merced
2010–2011	Graduate Studies University of Memphis (Memphis, TN)
2009	BA, *summa cum laude*, Psychology and English (minor: Spanish) With Distinction from the Harding University Honors College Harding University (Searcy, AR)

Peer-Reviewed Journal Articles

Mentees' names underlined.

Main, A., **Paxton, A.**, & Dale, R. (under review). An exploratory analysis of dynamic emotion regulation between mothers and adolescents during conflict discussions.

Abney, D., **Paxton, A.**, Dale, R., & Kello, C. (in press). Movement dynamics reflect a functional role for weak coupling and role structure in dyadic problem solving. *Cognitive Processing.*

Paxton, A., Rodriguez, K., & Dale, R. (2015). PsyGlass: Capitalizing on Google Glass for naturalistic data collection. *Behavior Research Methods, 47*(3), 608-619.

Fusaroli, R., Perlman, M., Mislove, A., **Paxton, A.**, Matlock, T., & Dale, R. (2015). Timescales of massive human entrainment. *PLOS ONE, 10*(4), e0122742.

Abney, D., **Paxton, A.**, Kello, C., & Dale, R. (2014). Complexity matching in dyadic interaction. *Journal of Experimental Psychology: General, 143*(6), 2304-2315.

Paxton, A., & Dale, R. (2013). Argument disrupts interpersonal synchrony. *Quarterly Journal of Experimental Psychology, 66*(11), 2092-2102.

Paxton, A., & Dale, R. (2013). Frame-differencing methods for measuring bodily synchrony in conversation. *Behavior Research Methods, 45*(2), 329-343.

Tollefsen, D., Dale, R., & **Paxton, A.** (2013). Alignment, transactive memory, and collective cognitive systems. *Review of Philosophy and Psychology, 4*(1), 49-64.

Refereed Conference Proceedings

Paxton, A., Roche, J., & Tanenhaus, M. (2015). Communicative efficiency and miscommunication: The costs and benefits of variable language production. In D. C. Noelle, R. Dale, A. S. Warlaumont, J. Yoshimi, T. Matlock, C. D. Jennings, & P. P. Maglio (Eds.), *Proceedings of the 37th Annual Meeting of the Cognitive Science Society.* Austin, TX: Cognitive Science Society.

Paxton, A., & Dale, R. (2014). Leveraging linguistic content and debater traits to predict debate outcomes. In P. M. Bello, M. Guarini, M. McShane, & B. Scassellati (Eds.), *Proceedings of the 36th Annual Meeting of the Cognitive Science Society.* Austin, TX: Cognitive Science Society.

Paxton, A., Abney, D, Kello, C. T., & Dale, R. (2014). Network analysis of multimodal, multiscale coordination in dyadic problem solving. In P. M. Bello, M. Guarini, M. McShane, & B. Scassellati (Eds.), *Proceedings of the 36th Annual Meeting of the Cognitive Science Society.* Austin, TX: Cognitive Science Society.

Paxton, A., Roche, J. M., Ibarra, A., & Tanenhaus, M. K. (2014). Failure to (mis)–communicate: Linguistic convergence, lexical choice, and communicative success in dyadic problem solving. In P. M. Bello, M. Guarini, M. McShane, & B. Scassellati (Eds.), *Proceedings of the 36th Annual Meeting of the Cognitive Science Society.* Austin, TX: Cognitive Science Society.

Paxton, A., & Dale, R. (2013). Multimodal networks of interpersonal interaction and conversational contexts. In M. Knauff, M. Pauen, N. Sebanz, & I. Wachsmuth (Eds.), *Proceedings of the 35th Annual Meeting of the Cognitive Science Society.* Austin, TX: Cognitive Science Society.

Roche, J., **Paxton, A.**, Ibarra, A., & Tanenhaus, M. (2013). From minor mishap to major catastrophe: Lexical choice in miscommunication. In M. Knauff, M. Pauen, N. Sebanz, & I. Wachsmuth (Eds.), *Proceedings of the 35th Annual Meeting of the Cognitive Science Society.* Austin, TX: Cognitive Science Society.

Drew, A. H., **Paxton, A.**, Kello, C., & Dale, R. (2013). Complexity matching in dyadic interactions. In P. Passos, J. Barrieros, R. Cordovil, D. Araújo, & F. Melo (Eds.), *Studies in Perception and Action XII: Proceedings from the Seventeenth International Conference on Perception and Action.*

Technical Reports and Other Publications

Paxton, A., Dale, R., & Richardson, D. C. (in press). Social coordination of verbal and nonverbal behaviors. In P. Passos, K. Davids, and C. Jia Yi (Eds.), *Interpersonal coordination and performance in social systems.* Routledge.

Fusaroli, R., Perlman, M., Mislove, A., **Paxton, A.**, Matlock, T., & Dale, R. (2014). *Timescales of massive human entrainment.* arXiv:1410.8105 [physics.soc-ph].

Paxton, A., & Dale, R. (2013). *B(eo)W(u)LF: Facilitating recurrence analysis on multi-level language.* arXiv:1308.2696 [cs.CL].

Conference Presentations

Asterisk denotes presenter, if not presented by first author.
Mentees' names underlined.

Paxton, A., & Dale, R. (2015, November). *Data–driven theory: Using NLP and deep learning in metascientific analyses.* Paper presented at the 45th Annual Meeting of the Society for Computers in Psychology. Chicago, IL.

Duran, N., Fusaroli, R., & **Paxton, A.** (2015, November). *Assessing lexical, syntactic, and conceptual turn-by-turn alignment in conversations involving conflict and deception.* Paper presented at the 45th Annual Meeting of the Society for Computers in Psychology. Chicago, IL.

Main, A., Dale, R., & **Paxton, A.** (2015, July). *An exploratory analysis of dynamic emotional communication between parents and adolescents during conflict discussions.* Paper presented at the meeting of the International Society for Research on Emotion.

Paxton, A., & Dale, R. (2015, May). *Adaptive interpersonal dynamics in communication.* Paper presented at the 27th Annual Meeting of the Association for Psychological Sciences. New York, NY.

Fusaroli, R., Perlman, M., Mislove, A., **Paxton, A.**, Matlock, T., & Dale, R. (2015, May). *Timescales of massive human entrainment.* Paper presented at the International Conference of Computational Social Science. Helsinki, Finland.

Rodriguez, K., **Paxton, A.**,* & Dale, R. (2014, November). *Cutting the cord: Capitalizing on Google Glass for naturalistic interaction research.* Paper presented at the 44th Annual Meeting of the Society for Computers in Psychology. Long Beach, CA.

Paxton, A., & Dale, R.* (2014, November). *The effects of low-level distractors on the dynamics of conversation.* Paper presented at the 55th Annual Meeting of the Psychonomic Society. Long Beach, CA.

Paxton, A., Roche, J. M., Ibarra, A., & Tanenhaus, M. K. (2014, July). *Failure to (mis)–communicate: Linguistic convergence, lexical choice, and communicative success in dyadic problem solving.* Paper presented at the 36th Annual Meeting of the Cognitive Science Society. Quebec City, Canada.

Lichtenstein, P., **Paxton, A.**,* & Dale, R. (2014, July). *Hand–to–hand conflict and consensus: Gestural alignment in argumentative versus affiliative conversations.* Paper presented at the 6th meeting of the International Society for Gesture Studies. San Diego, CA.

Paxton, A., & Dale, R. (2013, November). Keeping time: Dynamics in text analysis. Paper presented at the 43rd annual meeting of the Society for Computers in Psychology. Toronto, Canada.

Paxton, A., & Dale, R. (2013, August). *B(eo)W(u)LF: Facilitating multi-level recurrence analysis in language.* Paper presented at the 5th Recurrence Plot Symposium, Chicago, IL.

Paxton, A., & Dale, R. (2013, July). *Multimodal networks of interpersonal interaction and conversational context.* Paper presented at the 35th annual meeting of the Cognitive Science Society. Berlin, Germany.

Dale, R., **Paxton, A.**, & Duran, N. (2013, May). *How interactive goals shape the coordination of body and speech during conversation.* Paper presented at the 25th annual meeting of the Association for Psychological Science. Washington, DC.

Paxton, A., & Dale, R. (2012, November). *Linguistic alignment in debate.* Paper presented at the 42nd annual meeting of the Society for Computers in Psychology. Minneapolis, MN.

Dale, R., & **Paxton, A.** (2012, August). *Eigendialog: Bernstein's problem in human interaction.* Paper presented at the Guy Van Orden Workshop on Cognition and Dynamics. University of Connecticut, Storrs, CT.

Loan, A. (2009). *Respondent residency and survey prompt on community's perception.* Paper presented at the annual Arkansas Student Psychology Symposium. Siloam Springs, AR.

Loan, A. (2008). *Ethnicity of respondent and image on perception of adolescent's self–esteem.* Paper presented at the annual Arkansas Student Psychology Symposium. Jonesboro, AR.

Refereed Posters

Asterisk denotes presenter, if not presented by first author.

Paxton, A.,* Roche, J.,* & Tanenhaus, M. (2015, July). *Communicative efficiency and miscommunication: The costs and benefits of variable language production.* Poster presented at the 36th Annual Meeting of the Cognitive Science Society, Quebec City, Canada.

Paxton, A., & Dale, R. (2014, July). *Leveraging linguistic content and debater traits to predict debate outcomes.* Poster presented at the 36th Annual Meeting of the Cognitive Science Society, Quebec City, Canada.

Paxton, A., Abney, D. H., Kello, C. T., & Dale, R. (2014, July). *Network analysis of multimodal, multiscale coordination in dyadic problem solving.* Poster presented at the 36th Annual Meeting of the Cognitive Science Society, Quebec City, Canada.

Abney, D. H., **Paxton, A.**, Kello, C. K., & Dale, R. (2014). *Multimodal and multiscale interpersonal interaction in a joint problem solving task.* Poster presented at the 26th Annual Meeting of the American Psychological Society, San Francisco, CA.

Roche, J., **Paxton, A.**,* Ibarra, A., & Tanenhaus, M. (2013, August). *From minor mishap to major catastrophe: Lexical choice in miscommunication.* Poster presented at the 35th annual meeting of the Cognitive Science Society. Berlin, Germany.

Paxton, A., & Dale, R. (2013, May). *Breakdown: Conflict's fundamental reorganization of coordinated systems.* Poster presented at the 25th annual meeting of the Association for Psychological Science, Washington, DC.

Paxton, A., & Dale, R. (2012, November). *Integrating body and speech in conversational contexts.* Poster presented at the 53rd annual meeting of the Psychonomic Society, Minneapolis, MN.

Paxton, A., & Dale, R. (2011, November). *Alignment and argument.* Poster presented at the 52nd annual meeting of the Psychonomic Society, Seattle, WA.

Paxton, A., & Dale, R. (2011, November). *Multimodal synchrony: Tracking body and voice in an affordable behavioral recording setup.* Poster presented at the 41st annual meeting of the Society for Computers in Psychology, Seattle, WA.

Open–Submission Posters

Asterisk denotes presenter, if not presented by first author.

Abney, D.H., **Paxton, A.**, Kello, C.T., & Dale, R. (2013, August). *Complexity matching in dyadic interaction.* Poster presented at the 35th annual meeting of the Cognitive Science Society, Berlin, Germany.

Loan, A., & Dale, R. (2011, June). *Coordinating arguments: Embodied synchrony in argumentative and affiliative interactions.* Poster presented at the American Psychological Association's Advanced Training Institute for Nonlinear Methods, Cincinnati, OH.

Loan, A., Cossel, T. K., Tillery, R., Schoffstall, C. L., & Cohen, R. (2010, October). *Who's online? Boys' and girls' computer use.* Poster presented at the annual meeting of the Tennessee Psychological Association, Nashville, TN.

Invited Talks and Lectures

Paxton, A. (2015, October). *Interpersonal dynamics: Exploring conversation as a dynamical system.* Cognitive Science Colloquium, Department of Psychology, University of Memphis, Memphis, TN.

Paxton, A. (2015, May). *Scales of influence: How conflict changes bodies, voices, and minds.* Computational Cognitive Science Lab, University of California, Berkeley, Berkeley, CA.

Paxton, A. (2015, April). *Conversation: Complex system, complex signals.* Cognitive Science Brown Bag, Department of Psychological Sciences, Kent State University, Kent, OH.

Paxton, A. (2015, April). *PsyGlass: Using Google Glass to quantify conversation and interaction.* College of Education, Health, and Human Services, Kent State University, Kent, OH.

Paxton, A. (2015, February). *Conflict: An exploration of context-dependent behavioral coordination.* Department of Psychology Colloquium, University of California, Santa Cruz. Santa Cruz, CA.

Paxton, A. (2014, September). *Here for an argument: Conflict in laboratory and real–world settings.* CogNetwork Meeting, University of California, Berkeley. Berkeley, CA.

Paxton, A. (2013, November). *Exploring interaction through conflict.* Department of Psychology, University of Rochester. Rochester, NY.

Paxton, A. (2013, November). *Conflict as joint action.* Lecture for BCS 310 (Senior Seminar: Joint Action), University of Rochester. Rochester, NY.

Workshops

Paxton, A. (2013, November). *An introduction to cross-correlation.* Workshop for Department of Psychology, University of Rochester, Rochester, NY.

Local Presentations

Asterisk denotes presenter, if not presented by first author.
Mentees' names underlined.

Oakes, B.,* Patel, P.,* **Paxton, A.**, & Dale, R. (2015, March). *Influence of visual cues in language production.* Poster presented at the 8^{th} annual Research Week, University of California, Merced, CA.

Carey, K.,* Willson, K.,* **Paxton, A.**, & Dale, R. (2015, March). Kinesics of common conversations. Poster presented at the 8^{th} annual Research Week, University of California, Merced, CA.

Paxton, A., & Dale, R. (2013, March). *Contextual effects on speech and movement patterns in conversation.* Poster presented at the 6^{th} annual Research Week, University of California, Merced, CA.

Loan, A. (2008). *"But words can never hurt me": The psychological role of Nadsat in* A Clockwork Orange. Honors thesis presented and defended, English Department, Harding University, Searcy, AR.

Funding and Awards

2015	Cognitive and Information Sciences Research Award ($900) University of California, Merced
2015	Cognitive and Information Sciences Travel Award ($800) University of California, Merced
2015	Cognitive and Information Sciences Summer Fellowship ($2,250) University of California, Merced
2014	Cognitive and Information Sciences Travel Fellowship ($1,050) University of California, Merced
2014	Cognitive and Information Sciences Summer Fellowship ($3,800) University of California, Merced
2013	Cognitive and Information Sciences Graduate Award ($1,180) University of California, Merced
2013	Psychonomic Society Travel and Networking Award ($1,000) Women in Cognitive Science
2013	Center for Humanities Individual Research Grant ($2,000) University of California, Merced
2013	Cognitive Science Society Student Travel Grant ($599) Robert J. Glushko and Pamela Samuelson Foundation
2013	Student Caucus Travel Assistance Award ($200) Association for Psychological Science
2013	Cognitive and Information Sciences Summer Workshop Fellowship ($750) University of California, Merced
2013	Cognitive and Information Sciences Travel Fellowship ($2,000) University of California, Merced
2013	Cognitive and Information Sciences Summer Fellowship ($2,500) University of California, Merced
2013	Graduate Student Nominee, Outstanding Woman of UC Merced University of California, Merced

2012	John Castellan Award for Best Student Paper Society for Computers in Psychology
2012	Summer Training Scholarship ($1,200) University of California, Merced
2012	Graduate Division General Fellowship ($3,885) University of California, Merced
2011	Graduate Student Coordinating Committee Travel Award University of Memphis ($400)
2009	Who's Who Among Students in American Universities and Colleges
2009	Outstanding Research Award for the Behavioral Sciences Department Harding University
2005–2009	Dean's List Harding University
2005–2009	Arkansas Distinguished Governor's Scholar ($40,000)
2005–2009	Full Tuition National Merit Scholarship Harding University
2005	National Merit Scholar

Professional Affiliations

2015–*present*	Psychonomic Society (Student Member)
2013–*present*	Women in Cognitive Science
2013–*present*	Cognitive Science Society (Graduate Student Member)
2012–*present*	Association for Psychological Science (Graduate Student Affiliate)
2011–*present*	Society for Computers in Psychology
2007–*present*	Psi Chi
2011, 2013	American Psychological Association (Graduate Student Affiliate)
2008-2009	Alpha Chi Honor Society
2007-2009	Sigma Tau Delta
2005-2006	Phi Eta Sigma
2005-2009	American Studies Institute

Teaching Experience

Instructor of Record

Summer 2015	Research Methods (COGS 105) University of California, Merced (Merced, CA)

Teaching Assistant

Spring 2015	Research Methods (COGS 105) Instructor of Record: Dr. Rick Dale

	University of California, Merced (Merced, CA)
Fall 2014	Modern Everyday Cognition (COGS 127) Instructor of Record: Dr. Rick Dale University of California, Merced (Merced, CA)
Spring 2014	Complex Adaptive Systems (COGS 180) Instructor of Record: Dr. Michael Spivey University of California, Merced (Merced, CA)
Fall 2013	Introduction to Philosophy (PHIL 001) Instructor of Record: Dr. Rolf Johansson University of California, Merced (Merced, CA)
Spring 2013	Cognitive Neuroscience (COGS 130) Instructor of Record: Dr. Anne Warlaumont University of California, Merced (Merced, CA)
Fall 2012	Judgment & Decision Making (COGS/ECON/MGMT/POLI 153) Instructor of Record: Dr. Evan Heit University of California, Merced (Merced, CA)
Fall 2011	Philosophy of Cognitive Science (COGS/PHIL 110) Instructor of Record: Dr. Jeff Yoshimi University of California, Merced (Merced, CA)
Fall 2010	Child Psychology (PSYC 3103) Instructor of Record: Dr. Theresa Okwumabua University of Memphis (Memphis, TN)
Fall 2008	Departmental Teaching Assistant Psychology Department Harding University (Searcy, AR)

Additional Related Work

2008–2009	University Tutor Academic Resource Center Harding University (Searcy, AR)

Paid Research Experience

December 2014–January 2015	Graduate Research Assistant Dr. Rick Dale University of California, Merced (Merced, CA)
May–August 2013	Graduate Research Assistant Dr. Rick Dale University of California, Merced (Merced, CA)
December 2012–January 2013	Graduate Research Assistant Dr. Rick Dale University of California, Merced (Merced, CA)
January–August 2012	Graduate Research Assistant Dr. Rick Dale

	University of California, Merced (Merced, CA)
January–August 2011	Graduate Research Assistant Dr. Rick Dale University of California, Merced (Merced, CA)

Professional Service

2013–2015	Subject pool coordinator and SONA Systems administrator University of California, Merced (Merced, CA)
2013–2015	Member of Institutional Review Board University of California, Merced (Merced, CA)
2015	Reviewer: *Behavior Research Methods*; *Cognitive Processing*; *Journal of Nonverbal Behavior*; *PLOS ONE*
2015	Volunteer at the 37th annual meeting of the Cognitive Science Society
2015	Founder, Graduate Student Writing Club University of California, Merced (Merced, CA)
2014	Reviewer: *Cognitive Science*; *PLOS ONE*; *Behavior Research Methods*
2014	Volunteer at the 44th annual meeting of the Society for Computers in Psychology
2013	Ad hoc reviewer: *Applied Psychophysiology and Biofeedback*; *Behavior Research Methods*; *Current Biology*; *Journal of Experimental Psychology: General*
2013	Volunteer at the 25th annual meeting of the Association for Psychological Science
2013	Reviewer: Association for Psychological Science Student Caucus's Student Research Award
2012	Volunteer at the 42nd annual meeting of the Society for Computers in Psychology
2012	Ad hoc reviewer: *Speech Communication*
2012	Co-organizer for the Cognitive and Information Sciences Graduate Student and Faculty Meeting seminar series University of California, Merced (Merced, CA)
2011	Secretary for the Graduate Student Coordinating Committee University of Memphis (Memphis, TN)
2010–2011	Subject pool coordinator and SONA systems administrator University of Memphis (Memphis, TN)
2006–2009	Member of Academic Integrity Committee for revising academic standards Harding University (Searcy, AR)
2007	Statistics lab proctor Harding University (Searcy, AR)

Training and Unpaid Research Experience

2014	Dan Mirman's Introduction to Growth Curve Modeling Workshop (36th Annual Meeting of the Cognitive Science Society, Quebec City, Canada)
2013	American Psychological Association's Advanced Training Institute for Exploratory Data Mining in Behavioral Research (Davis, CA)
2012	Office of Research Development Services Workshop Series on Writing Competitive Research Proposals (University of California, Merced)
2012	Guy Van Orden Workshop on Cognitive Dynamics (University of Connecticut)
2012	Sixth Annual Empirical Methods for Cognitive Linguistics Workshop (EMCL 6)
2011	American Psychological Association's Advanced Training Institute for Nonlinear Methods (Cincinnati, OH)
2011	Statistical programming seminar (University of Memphis)
2008	Designed an online developmental psychology course and associated materials with Dr. Glen Adams (Harding University)

Mentoring and Diversity

2013–*present*	Graduate student mentor in Peer Mentor Program (University of California, Merced)
2015	Mentees K. Carey and K. Willson: Winners of 8th annual Research Week Undergraduate Poster Competition (University of California, Merced)
2012–2013	Member of Board of Directors for Merced RRDG, a 501(c)(3) nonprofit organization dedicated to promoting athleticism and health behaviors in women and children
2008, 2010, 2011	Volunteer counselor at Camp Concern, a summer camp for urban youth in Pittsburgh, PA
2008–2009	Circle K International

Press

September 2013	Grad research at CogSci '13. *CogSci @ UC Merced.*
March 2012	A student of synchrony. *gradPSYCH Magazine.*
March 2012	Cognitive science student studies conflict. *University News.*
March 2012	UC Merced Connect: Student studying subconscious synchronization. *Merced Sun-Star.*

Abstract

Interpersonal coordination broadly captures the ways in which interacting individuals become more similar over time in their behavior, cognition, and affect over time. The research area around interpersonal coordination is poised to yield unique insights into questions of human communication, interaction, and social behavior. As a field, interpersonal coordination still has immense room to grow—providing an exciting challenge to interdisciplinary researchers. Interpersonal coordination has enjoyed an explosion of interest in recent years, making these challenges even more urgent. Here, in collaboration with various coauthors, I present three projects that address some of the key theoretical, methodological, and experimental issues facing the research area today.

First, I present a data-driven exploration of the terminology surrounding interpersonal coordination (Paxton & Dale, in preparation). From alignment to synergy, there are handfuls of terms that are used to describe this social phenomenon, with little to no agreement across the field on their relation to one another. Using scientometric and corpus analysis tools, the first project analyzes a corpus of thousands of abstracts on related research to shed some light on the implicit structure in the data.

Next, I introduce PsyGlass, an open-source application that turns Google Glass into a tool for naturalistic data collection (Paxton, Rodriguez, & Dale, 2015, Behavior Research Methods). The inherently social nature of interpersonal coordination poses an interesting problem to cognitive scientists who must attempt to balance external validity with experimenter control. PsyGlass is designed for naturalistic exploration of theory-driven questions in interpersonal interaction by facilitating surreptitious data collection and moment-to-moment control over participant visual stimuli.

Finally, I explore how context modulates patterns of coordination in gaze patterns (Paxton, Dale, & D. C. Richardson, in preparation). This chapter contributes to emerging work that explores how higher-level social factors can alter patterns of coordination by focusing on conflict.

This dissertation, *Coordination: Theoretical, Methodological, and Experimental Perspectives*, is submitted by Alexandra Paxton in 2015 in partial fulfillment of the degree Doctor of Philosophy in Cognitive and Information Sciences at the University of California, Merced, under the guidance of dissertation committee chair Rick Dale.

Chapter 1

Introduction

1.1 Introduction

Our lives are marked, supported, and enriched by social interaction. As part of a complex social ecosystem, we are often aware of the powerful effects that our behavior can have on others. We tend to be less aware, however, of our much more subtle ties—the interconnectedness of our language, movement, and emotion with around us. The field of *interpersonal coordination*[1] characterizes that subtle web of connectedness and the low "hum" of social resonance.

1.2 Interpersonal Coordination

As an exciting but relatively young frontier in cognitive science, the interdisciplinary research area that has sprung up around interpersonal coordination is rife with important unsolved issues. In this dissertation, I am chiefly interested in exploring pressing issues in three main considerations: theoretical perspectives, methodology, and experimental investigations. Each of these very broad areas still have enormous room for growth as the field matures; the present work is chiefly concerned with one or two issues within each area.

1.2.1 Theoretical Perspectives

From its immediate origins in clinical (Condon & Ogston, 1966) and developmental (Condon & Sander, 1974) psychology—and more distant origins in early health psychology and public health (Glad & Adesso, 1976; Polansky, Lippitt, & Redl, 1950; Wheeler, 1966)—the study of interpersonal coordination has thrived in recent decades. Known by various names, related research into interpersonal coordination has spread to include a wide variety of perspectives, from affect (e.g., Butler, 2011) to movement (e.g., M. J. Richardson, Marsh, Isenhower, Goodman, & Schmidt, 2007) to language (e.g., Niederhoffer & Pennebaker, 2002). Although these perspectives largely evolved distinct from one another, theoretical proposals (e.g., Pickering & Garrod, 2004) and experimental work (e.g., Paxton, Abney, Kello, & Dale, 2014) have begun to integrate our understanding of coordination across communication modalities, forming a picture of coordination as a multimodal and multiscale phenomenon.

[1] As I discuss in greater detail later, I understand there is a distinct lack of agreement within the field on what to call this phenomenon. For ease and brevity, I will use "coordination" to refer to it during the introduction. Subsequent chapters will each include operational definitions for the phenomenon.

At the same time, new perspectives are pushing the field to reexamine the structure of interpersonal coordination. Coordination has largely revolved around the study of similar affect, behavior, and cognition performed in temporal proximity, but ideas of interpersonal *synergies* (Riley, Richardson, Shockley, & Ramenzoni, 2011) have begun to challenge this dominant perspective. Rather than interpreting coordination as a simple "similar is better" view, the emerging theoretical viewpoint suggests that interpersonal coordination is an adaptive emergent property of interaction that is context-sensitive and highly dynamic (Abney, Paxton, Dale, & Kello, in press). While still in its early stages, this idea has been increasingly supported by work demonstrating the context-sensitivity of coordination (e.g., Paxton & Dale, 2013a; Miles, Griffiths, Richardson, & Macrae, 2010) and highlighting how harmful simple similarity can be in some settings (e.g., Fusaroli et al., 2012; Main, Paxton, & Dale, under review).

This research area has grown immensely due to increased popularity over the past several decades. Its fundamentally interdisciplinary nature ties together lines of research from numerous fields, from psychotherapy (e.g., Nagaoka & Komori, 2008) to marketing (e.g., Ramanathan & McGill, 2007). This fractured history poses an interesting challenge to the field: Not only are there more than a dozen terms used to describe the phenomenon[2], but there is little to no consensus about their relation to one another. As the field grows and grapples with the very nature of coordination, creating and understanding the language of coordination becomes increasingly urgent.

1.2.2 Methodology

The varied origins of the research area—along with its spreading influence—have led to the study of coordination through a variety of methodologies. For example, researchers have approached affective coordination by analyzing video-recorded interactions (e.g., Main et al., under review; Sadler, Ethier, Gunn, Duong, & Woody, 2009; Randall, Post, Reed, & Butler, 2013) or by exploring changes in cortisol (e.g., Saxbe & Repetti, 2010). Quantifications of linguistic coordination include linguistic content (e.g., Niederhoffer & Pennebaker, 2002; Fusaroli et al., 2012), acoustic signals (e.g., Abney, Paxton, Dale, & Kello, 2014; Paxton et al., 2014), or modeling meaning in social media activity (e.g., Garimella, Morales, Gionis, & Mathioudakis, 2015). Naturally, the operationalization of coordination changes with the specific communication channel under consideration, and coordination research in nearly all modalities is adapting to changes in technology and society.

Accordingly, movement coordination is undergoing significant change as technology begins to offer alternatives to a traditionally labor-intensive process. Some of the very earliest work in this area quantified interpersonal coordination through meticulous frame-by-frame hand-coding of video recordings (Condon & Ogston, 1966; Condon & Sander, 1974). Hand-coding is still practiced, although often in more moderate forms—like watching videos to count or chart specific behaviors (e.g., Chartrand & Bargh, 1999; Louwerse, Dale, Bard, & Jeuniaux, 2012; Grammer, Kruck, & Magnusson, 1998). As computational power increases and high-resolution technology becomes cheaper, automated measures of behavioral coordination are becoming increasingly widespread—including frame-differencing measures for analyzing video (e.g., Paxton & Dale, 2013b) and motion-tracking systems (e.g., M. J. Richardson et al., 2007).

Even as methods improve for quantifying coordination, research on coordination—especially movement coordination—is still marked by a steep trade-off between experimental control and external validity. Many of the experimental manipulations needed to better understand important parameters of coordination often have required stilted or

[2] An inexhaustive list includes accommodation, adaptation, alignment, contagion, congruency, coordination, coupling, entrainment, imitation, mimicry, social tuning, synchrony, and synergy.

artificial laboratory setups, somewhat removing the laboratory behavior from its natural habitat. Conversely, more observational setups can capture slice-of-life coordination but are therefore fairly limited in their ability to create settings that can push coordination outside its usual parameters. With this trade-off in current technologies, pioneering new methods may help bridge the gap between naturalistic paradigms and experimental control.

1.2.3 Experimental Investigations

As coordination research matures as a field, lines of inquiry within it are beginning to expand, moving beyond questions of *whether* we coordinate to deeper questions of *how* and *why* we coordinate. Some of the more popular interests include how individual traits (e.g., Tschacher, Rees, & Ramseyer, 2014; Bos, Bouhuys, Geerts, Van Os, & Ormel, 2006) or different relationship qualities (e.g., Main et al., under review; Ramseyer & Tschacher, 2011) affect coordination. Relatively less focus has historically been placed on larger-scale contextual factors. The majority of previous research explores coordination during task-based (e.g., Hove & Risen, 2009; Louwerse et al., 2012), affectively neutral (e.g., Condon & Sander, 1974), or affiliative (e.g., Koss & Rosenthal, 1997) interactions.

This is not universally the case, however. One of the earliest lines of research emerged with ideas about how broader social factors—especially social group membership—could modulate coordination (e.g., Giles, Taylor, & Bourhis, 1973). Other work has explored the importance of social pacts and perceptions in influencing coordination across both high- and low-level behavioral measures (e.g., Lakin, Chartrand, & Arkin, 2008; Miles et al., 2010; Miles, Lumsden, Richardson, & Macrae, 2011). To date, however, only a small slice of possible communicative contexts—whether people are interacting in friendly conversation, task-directed interactions, or even arguments—have been explored.

Decades of previous research have demonstrated that coordination exists across a number of modalities during interaction (see Chapter 2). The challenge facing the field now is to understand what function coordination might serve and how it emerges. One step in this vital new path in the evolution of coordination is to understand how communicative context shapes coordination.

1.3 Motivation and Previous Work

Over the past several years, my research program has quantified the context-dependence of multimodal behavior during interaction. This work has primarily explored how conflict (as a communicative context) changes the nature of behavior, communication, and interaction (e.g., Abney et al., 2014; Paxton & Dale, 2013a; Main et al., under review; Paxton & Dale, 2013c, in preparation). Studies of other communicative contexts (e.g., task-based interactions; Abney et al., in press; Paxton, Roche, & Tanenhaus, 2015; Paxton et al., 2014) support this primary focus, highlighting the context-dependent nature of interpersonal dynamics by providing a contrasting contextual lens.

Coordination has been one of my strongest influences in shaping my perspective, methodology, and questions, and I have been grappling with deep underlying issues within interpersonal coordination. Some of my earliest work provided researchers with an open-source tool to analyze movement in video recordings (Paxton & Dale, 2013b) and presented the first theoretically motivated exploration of coordination and conflict (Paxton & Dale, 2013a). Interpersonal coordination has since remained a core concern within my research program. This dissertation carries and extends this central interest by addressing pressing issues within the coordination literature.

1.4 The Present Work

This dissertation is centered on questions within the theoretical, methodological, and experimental domains of the coordination research area. These are highly interrelated areas of growth for this research area. As a cognitive scientist with a computational social science perspective, I feel these three strands of the research area should also be reflected in my own work—simultaneously pushing theory, methods, and experimental findings within coordination.

The first section confronts the mystery surrounding the terminology of coordination with data-driven perspectives on the various terms used to describe it. The wide variety of coordination-related terms has led to a scattered research area, and researchers have no agreed-upon understanding of what each term means nor how each term relates to one another. Building from previous subjective efforts to classify these terms (Butler, 2011; Delaherche et al., 2012), this section uses multiple semantic analyses to understand the state of the terminological field.

The next section introduces PsyGlass, a new method for both quantifying behavior and giving experimenters moment-to-moment control over participant stimuli during naturalistic paradigms. Like previous work (Paxton & Dale, 2013b), PsyGlass is meant to facilitate objective quantification of behavior even for researchers with relatively little funding or programming experience—but it adds the ability for researchers to present participants with on-the-fly instructions, subtle stimuli, and more. Although it can be used to address a variety of research questions, PsyGlass was developed to help bridge the gap between naturalistic settings and strong experimental control in interpersonal coordination research. This chapter provides an overview of wearable technology in cognitive science, outlines PsyGlass, and presents a brief study on interpersonal coordination as an example of how PsyGlass can be used to extend traditional questions in cognitive science.

The final section looks at how patterns of gaze coordination are modulated by communicative context. Results from previous work have demonstrated that gaze coordination occurs between interlocutors during speech and suggested that this gaze coordination is causally linked to comprehension (D. C. Richardson & Dale, 2005). However, this previous work only examined relatively neutral conversational contexts. At the same time, the support for a causal relationship between gaze coordination and comprehension provides an intriguing test ground for exploring the effects of context. This is especially true for conflict, a conversational context demonstrated to reduce or break interpersonal coordination in movement (Paxton & Dale, 2013a) and speech (Abney et al., 2014; Paxton & Dale, 2013c). This final section explores how context—whether participants agree or disagree about a given topic—modulates gaze coordination patterns.

Chapter 2

A data–driven approach to disambiguating the terminology of interpersonal similarity

2.1 Introduction

A relatively new field of study has emerged over the past several decades, investigating how and why interacting individuals become more similar in affect, behavior, and cognition over time. These researchers approach the question from one or more of a number of diverse perspectives: clinical psychology (e.g., Condon & Ogston, 1966; Nagaoka & Komori, 2008; Ramseyer & Tschacher, 2011), cognitive psychology (e.g., Chartrand & Bargh, 1999; Dale, Kirkham, & Richardson, 2011), developmental psychology (e.g., Bernieri, Reznick, & Rosenthal, 1988; Condon & Sander, 1974; Criss, Shaw, & Ingoldsby, 2003), emotion and rapport (e.g., Grammer et al., 1998; LaFrance, 1979; Lakin & Chartrand, 2003), joint action (e.g., Knoblich & Jordan, 2003; Tollefsen, Dale, & Paxton, 2013; Valdesolo, Ouyang, & DeSteno, 2010), psycholinguistics (e.g., Brennan & Clark, 1996; Niederhoffer & Pennebaker, 2002; Pickering & Garrod, 2004), motor control (e.g., M. J. Richardson et al., 2007; Riley et al., 2011; Shockley, Santana, & Fowler, 2003; Turvey, 1990), neuroscience (e.g., Hasson, Ghazanfar, Galantucci, Garrod, & Keysers, 2012; Konvalinka & Roepstorff, 2012; Stephens, Silbert, & Hasson, 2010), physiology (e.g., Helm, Sbarra, & Ferrer, 2012; Saxbe & Repetti, 2010), social perception (e.g., Bernieri, Davis, Rosenthal, & Knee, 1994), and speech and language (e.g., McFarland, 2001).

Attention from so many fields has led to a deeper understanding of the phenomenon, but it has also created a constellation of terms with no clear set of relations among them. This has led to the growth of a series of splintered literatures across individual research areas. While some researchers appear to use the terms interchangeably, others appear to use specific terms to denote specific theoretical stances. However, there has been to date no consensus about how these terms should be treated.

The interdisciplinarity and multimodality of this research area is an incredible strength with great possibilities. We believe it is in the best interest of the research area to begin to understand and perhaps even resolve these differences. We start our work with a review of the current state of this research area by presenting some of the most common terms and important findings related to each. We review eight unique terms, presented in alphabetical order: accommodation, adaptation, alignment, the chameleon effect (or mimicry), contagion, mirroring (and the mirror neuron system), synergy (or coordinative structures), and synchrony.[1]

2.1.1 Accommodation

Communication Accommodation Theory (CAT)—also known as *accommodation theory* and *Speech Accommodation Theory*—was one of the earliest attempts to establish a theory for this phenomenon. CAT emerged with a strong eye interpersonal factors to help explain the how social forces at multiple scales affect speech (e.g., Bourhis, Giles, & Lambert, 1975; Giles, Taylor, & Bourhis, 1977; Giles, Coupland, & Coupland, 1991). Many of the first works were concerned with the strategic *convergence* and *divergence* of speech according to contextual demands, including social distance between speaker and listener and social perception of the speaker by the listener (e.g., Bourhis et al., 1975; Giles, 1973; Giles et al., 1973; Larsen, Martin, & Giles, 1977; Simard, Taylor, & Giles, 1976). Giles (1973) suggested that interlocutors strengthen interpersonal bonds through the use of more similar speech (i.e., convergence) and that interlocutors may distance themselves from one another through the adoption of more distinct speech (i.e., divergence).

The underlying assumptions in those views—that convergence and divergence are (a) to some extent intentional and (b) inextricably tied to social dynamics and context—became and remained central to CAT (e.g., Beňuš et al., 2014). Later work expanded CAT to explore additional sociolinguisic concerns, from implicit cultural factors (Babel, 2010) to maintaining cultural distinctiveness (Clachar, 1997) to listeners' causal attributions for speakers' convergence or divergence (Simard et al., 1976). CAT has also grown to include additional communication modalities (for review, see Giles et al., 1991).

2.1.2 Adaptation

Perhaps the most unique aspect of the *partner-specific adaptation* (also called *talker-specific adaptation* or simply *adaptation* view is its strong stance on the intentionality of the process (e.g., Brennan & Hanna, 2009). The adaptation view is loosely connected across several terms but is most recognizable in the use of several key terms and associated core beliefs. *Common ground*—the shared goals and information between interlocutors—is essential to successful interaction, and interlocutors continue the *grounding* process throughout an interaction (e.g., Brennan, Galati, & Kuhlen, 2010; H. H. Clark & Krych, 2004). Through grounding, interlocutors intentionally *adapt* their behavior to partner- and situational-specific needs (e.g., Brennan & Hanna, 2009; Bangerter & Clark, 2003; Rogers, Fay, & Maybery, 2013). One of the most noticeable avenues of adaptation is through interlocutors' use of *conceptual* or *referential pacts*, mutually adopted terms and phrases that create a communicative shorthand based on the interlocutors' shared history (e.g., Brennan & Clark, 1996; Brennan et al., 2010).

In this view, both parties in conversation—speakers and listeners—are actively involved in the joint creation of meaning and in the adaptation process. Speakers engage in audience design to facilitate listener understanding by selectively including or excluding information (e.g., Galati & Brennan, 2010) while monitoring listeners' comprehension (e.g., H. H. Clark & Krych, 2004). Meanwhile, listeners employ partner-specific

[1]We recognize that the terms listed are not exhaustive, that some individuals use these terms in other ways, and that some individuals use several terms interchangeably. This is emblematic of the current terminological uncertainty that we hope to highlight in this paper.

processing that helps them to quickly adapt to speakers' idiosyncrasies (e.g., accents; Trude & Brown-Schmidt, 2012 and the dyad's interaction history (e.g., referential pacts; Brown-Schmidt, 2009. Like CAT (e.g., Giles et al., 1991), adaptation has its roots in linguistic or lexical behaviors (e.g., accents; Brennan & Clark, 1996. Recent work has explored adaptation in other aspects of communication, like gesture (e.g., Mol, Krahmer, Maes, & Swerts, 2012) and speech perception (e.g., Trude & Brown-Schmidt, 2012).

2.1.3 Alignment

The *interactive alignment theory* proposed by (Pickering & Garrod, 2004) is perhaps one of the best-known theories in this area. Interpersonal alignment relies heavily on priming as a causal mechanism (e.g., Branigan, Pickering, & Cleland, 2000; Cleland & Pickering, 2003; Ferreira & Bock, 2006; Mol et al., 2012). Alignment is accordingly considered a largely unintentional process (Pickering & Garrod, 2004). Although the interactive alignment account grew out of a psycholinguistic perspective, Pickering and Garrod (2004) propose even in their seminal work that individuals should align across multiple timescales (e.g., phonemes, lexical choice, syntactic construction) and modalities (e.g., speech, cognition). The modalities and timescales are believed to support one another, such that alignment along one dimension can increase alignment in other dimensions (e.g., Menenti, Pickering, & Garrod, 2012; Reitter, Moore, & Keller, 2006). This explicit multidimensionality is one of the most defining and unique elements of the theory.

The relative popularity of the interactive alignment account has led to its application in a number of fields and to a number of questions. For example, recent efforts in neuroscience have sought possible neural mechanisms under the alignment account (Menenti et al., 2012) and have explored alignment of neural patterns during conversation (Hasson et al., 2012; Stephens et al., 2010). Advances in automated text analysis (e.g., Niederhoffer & Pennebaker, 2002) have facilitated questions of lexical and syntactic alignment of transcripts (e.g., of police interrogations in B. H. Richardson, Taylor, Snook, Conchie, & Bennell, 2014 and of online text (e.g., in multiparty health forums in Wang, Reitter, & Yen, 2014. However, the popularity of the view has led related terms—like "alignment"—to be used in situations in which no exclusive theoretical stance is denoted (e.g., Dale et al., 2011; Healey, Swoboda, Umata, & King, 2007).

2.1.4 Chameleon Effect or Mimicry

Introduced by Chartrand and Bargh (1999), the *chameleon effect*—also referred to as *unconscious human mimicry* or simply *mimicry*—relies upon the perception-action link in explaining the humans' tendencies to perform similar movements and adopt similar postures. Investigations on movement-based mimicry predated Chartrand and Bargh (1999)'s findings (e.g., Bavelas, Black, Lemery, & Mullett, 1986), but the term mimicry has since largely grown up around the chameleon effect. Despite its early focus on movement specifically, the area has come to encompass other forms of mimicry as well (e.g., language, emotion; Chartrand & Dalton, 2008. From its first appearance, the chameleon effect has been centrally concerned with the (a) social implications and (b) evolutionary basis of behavioral similarity (e.g., Chartrand & Bargh, 1999; Lakin, Jefferis, Cheng, & Chartrand, 2003; van Baaren, Janssen, Chartrand, & Dijksterhuis, 2009). The chameleon effect often couches findings within the idea that mimicry breeds affiliation (e.g., Chartrand & Dalton, 2008). The link between similarity and rapport has been studied by researchers across the theoretical spectrum (e.g., Giles, 1973; Tickle-Degnen & Rosenthal, 1990), but the connection between mimicry and positive social emotions is perhaps most strongly emphasized by those within the chameleon effect area (e.g., van Baaren et al., 2009).

The emphasis the evolutionary significance of interpersonal behavioral similarities is another hallmark of research under this theory (e.g., Lakin et al., 2003). Mimicry's link to positive social emotions has been suggested as a means to signal in-group membership (e.g., Lakin et al., 2008), to deepen interpersonal (e.g., van Baaren et al., 2009) and group (e.g., Ashton-James, van Baaren, Chartrand, Decety, & Karremans, 2007) ties, and to increase prosocial behavior (e.g., Ashton-James et al., 2007; van Baaren, Holland, Kawakami, & van Knippenberg, 2004). Moreover, the chameleon effect posits that mimicry occurs unconsciously, as an almost automatic response to the social environment (e.g., Chartrand & Bargh, 1999; Chartrand & Dalton, 2008; van Baaren et al., 2009). Under this view, mimicry is believed to have evolved to support social interactions and basic survival at the group level by facilitating links between individuals without requiring more costly and overt social signaling (e.g., Lakin et al., 2003).

2.1.5 Contagion

Affective or *emotional contagion* describes the ways in which individuals affect and are affected by the emotional states of others (e.g., Hatfield, Cacioppo, & Rapson, 1993). Research supports contagion effects during interaction (e.g., Neumann & Strack, 2000; Pugh, 2001; Rozin & Royzman, 2001) and through more static, priming-based methods (e.g., Erisen, Lodge, & Taber, 2014). Suggested mechanisms for affective contagion include the perception-action link (e.g., McIntosh, 2006; Neumann & Strack, 2000) and the mirror neuron system[2] (e.g., Nummenmaa, Hirvonen, Parkkola, & Hietanen, 2008). However, recent analyses of social networks have demonstrated that affect can spread without direct observation (e.g., Kramer, Guillory, & Hancock, 2014), indicating that additional processes may play a role in contagion.

Behavioral contagion describes how complex behaviors spread across individuals, often with stronger allusions to biological contagion (e.g., Jones & Jones, 1995) than is seen in work on affective contagion. These behaviors are generally not the kinds of low-level behaviors traditionally targeted by work employing other terminology, like interpersonal synchrony (e.g., infants' overall body movements; Condon & Sander, 1974 or mimicry (e.g., finger tapping; Chartrand & Bargh, 1999. Instead, behavioral contagion tends to focus on higher-level behaviors with applied implications. For example, clinical investigations have examined behavioral contagion of suicide (Gould, Jamieson, & Romer, 2003) and antisocial behaviors (Wheeler, 1966); social explorations have targeted contagion of behaviors as varied as product adoption (Aral, Muchnik, & Sundararajan, 2009), voting (Bond et al., 2012), smoking (Glad & Adesso, 1976), and popularity (Marks, Cillessen, & Crick, 2012).

Contrasting with largely dyad-level analyses under other terminological umbrellas, researchers in contagion-based areas combine dyadic-level (e.g., Neumann & Strack, 2000; Nummenmaa et al., 2008; Pugh, 2001) and group- or population-level (e.g., Barsade, 2002; Glad & Adesso, 1976; Jones & Jones, 1995; Marks et al., 2012; Polansky et al., 1950) analyses of interpersonal influence. The increasing availability of online behavior and social network data has created new opportunities for both affective (e.g., Christakis & Fowler, 2013; Coviello et al., 2014; Kramer et al., 2014) and behavioral (Aral et al., 2009; Bond et al., 2012; Christakis & Fowler, 2013) contagion research that complement traditional investigations of face-to-face interaction.

[2]See "Mirroring and the mirror neuron system" section.

2.1.6 Mirroring and the Mirror Neuron System

First discovered in the F5 area of the macaque premotor cortex (Gallese, Fadiga, Fogassi, & Rizzolatti, 1996; Rizzolatti, Fadiga, Gallese, & Fogassi, 1996), *mirror neurons* in macaques fire during both the observation and the performance of primarily goal-directed, object-effector actions (for review, see Rizzolatti & Craighero, 2004. The search for human homologues has led to the postulation of a *mirror neuron system* (MNS). The proposed MNS includes several brain regions that, together, function similarly to mirror neurons: the superior temporal sulcus, the inferior frontal cortex, and the rostral part of the inferior parietal lobule (Iacoboni, 2005).

However, the human MNS appears to be more socially driven than the macaque mirror neurons. Unlike macaque mirror neurons (cf. Gallese et al., 1996; Rizzolatti et al., 1996, the MNS activates even when observing incidental (i.e., non-goal-directed; Rizzolatti & Craighero, 2004 or non-intended (e.g., tripping; Buccino et al., 2007 actions. Moreover, levels of MNS activation differ according to contextual factors, like an observer's level of expertise in the behavior (e.g., dancers and martial artists; Calvo-Merino, Glaser, Grèzes, Passingham, & Haggard, 2005) or the complementarity of behavior between observer and observed (e.g., grip shapes; Newman-Norlund, van Schie, van Zuijlen, & Bekkering, 2007). Coupled with activation in the limbic system and the insula, evidence suggests that the MNS is activated during the *mirroring* (or spontaneous imitation) of others' affective displays (e.g., L. Carr, Iacoboni, Dubeau, Mazziotta, & Lenzi, 2003; Iacoboni, 2005).

These capacities of the MNS have led to its adoption as an explanatory mechanism of various aspects of human social cognition, particularly empathy and action understanding (e.g., Calvo-Merino et al., 2005; L. Carr et al., 2003; Iacoboni, 2005; Oberman, Pineda, & Ramachandran, 2007; Oberman & Ramachandran, 2007; Pfeifer, Iacoboni, Mazziotta, & Dapretto, 2008). Some have criticized claims made by mirror neuron research as overreaching (e.g., Hickok, 2009) or as incomplete explanations of target phenomena (e.g., Hamilton, Brindley, & Frith, 2007). However, the mirror neuron system has found acceptance as a possible neural mechanism for the tendency toward interpersonal similarity (with varying degrees of explanatory power; cf. Brass & Heyes, 2005; Iacoboni, 2005) in several theoretical stances mentioned in the present article (e.g., Dijksterhuis, Smith, van Baaren, & Wigboldus, 2005; Nummenmaa et al., 2008; McIntosh, 2006; Menenti et al., 2012; Ramseyer & Tschacher, 2008; van Baaren et al., 2004), spanning both representational and embodied accounts of imitation (E. W. Carr & Winkielman, 2014; Pineda, 2008).

2.1.7 Synergy or Coordinative Structure

Borrowed from the motor control literature (e.g., Bernstein, 1967), the *interpersonal synergies* view posits that interacting individuals should adapt themselves flexibly to one another and to the needs of the situation (Riley et al., 2011). In the motor system, muscle *synergies* or *coordinative structures* reduce the effective degrees of freedom by creating soft-assembled muscle groupings that act as a single unit, diminishing the strain on motor control through lower *functional* degrees of freedom (e.g., d'Avella, Saltiel, & Bizzi, 2003; Tresch & Jarc, 2009; Turvey, 2007). Essentially, synergies minimize variability in task-relevant domains while allowing variability in non-relevant domains to range freely in the system's attempt to reach a goal (e.g., Kelso, Tuller, Vatikiotis-Bateson, & Fowler, 1984). This results in a goal-focused, context-sensitive, and perturbation-adaptive view of motor control (Turvey, 1990).

Interpersonal synergies apply these ideas beyond the individual to interpersonal interaction. Viewing the dyad as a soft-assembled system, the interpersonal synergies view suggests increasing interpersonal similarity alone may not necessarily result in the most optimal configuration for patterns of interpersonal interactions (Riley et al., 2011). Instead, a combination of complementarity and similarity of various communicative channels and behaviors may be required, as supported by recent experimental work (e.g., Fusaroli et al., 2012; Abney et al., in press). The structure of the interpersonal synergies—as with muscle synergies—are posited to be context-sensitive, resulting in a soft-assembled and adaptable dyadic system highly dependent on the individuals involved and the context demands (Dale, Fusaroli, Duran, & Richardson, 2014; Paxton, Dale, & Richardson, in press).

The idea of interpersonal synergies has since spread beyond its initial use in interpersonal motor or movement synergies (Black, Riley, & McCord, 2007; Riley et al., 2011; Ramenzoni, Riley, Shockley, & Baker, 2012; Abney et al., in press). Recent work has applied the idea to linguistics (Fusaroli et al., 2012; Fusaroli, Raczaszek-Leonardi, & Tylén, 2014) and multimodal communication (Paxton et al., 2014). Related work on flexible coordinative structures in social interaction or conversation more broadly (Schmidt & Richardson, 2008; Shockley, Richardson, & Dale, 2009)—although predating Riley et al.'s (2011) theoretical piece introducing interpersonal synergies—should be considered as stemming from the same originating field, as the phrase has a similar origin in the motor control literature (e.g., Kelso et al., 1984).

2.1.8 Synchrony

Synchrony—also known as *interactional synchrony* or *interpersonal synchrony*—is one of the oldest and most commonly used terms, again stemming from work on movement (Condon & Ogston, 1966; Condon & Sander, 1974). Work under this term tends to focus on *phase-locked* movement of specific effectors (e.g., finger tapping in Hove & Risen, 2009; hand movement in Macrae, Duffy, Miles, & Lawrence, 2008; arm movement in Miles et al., 2011; rocking in M. J. Richardson et al., 2007) or overall body movement (e.g., Nagaoka & Komori, 2008; Paxton & Dale, 2013a; Ramseyer & Tschacher, 2011). Research under these terms often target phase-locked relations between behavioral signals, linking it to the term *entrainment* (e.g., Miles, Nind, & Macrae, 2009; M. J. Richardson et al., 2007). However, synchrony also has been used during explorations of atemporal phenomena (e.g., written language use in Ireland & Pennebaker, 2010), behavior with looser temporal structure (e.g., subjective evaluations of movement tempo in Koss & Rosenthal, 1997), or non-movement phase-locked behavior (e.g., affect in Sadler et al., 2009; gesture and speech in Wagner, Malisz, & Kopp, 2014).

Interpersonal synchrony is often investigated with an eye to its social or communicative consequences. The rapport-synchrony link has been upheld in numerous articles (e.g., Bernieri et al., 1994; Hove & Risen, 2009; Cacioppo et al., 2014), and related work has tied synchrony to other social factors, like group cohesion (e.g., Wiltermuth & Heath, 2009; Miles et al., 2011), prosocial behaviors (e.g., Valdesolo et al., 2010; Cirelli, Einarson, & Trainor, 2014), or adherence to social norms (e.g., Miles et al., 2010). Improved mechanisms associated with communication—like improved memory (e.g., Macrae et al., 2008)—have also been associated with interpersonal synchrony. In light of these findings, it is unsurprising that interpersonal synchrony has been used as a lens to study outcomes in patient-clinician (e.g., Koss & Rosenthal, 1997; Nagaoka & Komori, 2008; Ramseyer & Tschacher, 2008, 2011) and parent-child (e.g., Bernieri et al., 1988; Criss et al., 2003; Main et al., under review) relationships.

2.1.9 The Present Study

This research area is currently divided by its scattered terminology. To the authors' knowledge, there has only been one formal attempt to create a taxonomy for this research area (Delaherche et al., 2012).[3] While an important first step, it was largely subjective: The definitions of each term and their relations to one another were grounded in existing work but were nevertheless based on the authors' own categorizations.

To this end, we here present a first attempt to objectively relate existing terms within the field to one another, inspired by recent pushes in metascientific or scientometric analyses (e.g., Griffiths & Steyvers, 2004; Bergmann, Dale, Sattari, Heit, & Bhat, accepted). Using abstracts pulled from a wide variety of research works related to this area, we use automated classification techniques to uncover the existing implicit relationships across the terms as they are currently used. This allows the work within this research area to speak for itself, rather than creating a pre-specified structure through which the existing literature should be viewed.

The present study analyzes 11 terms: *accommodation*, *adaptation*, *alignment*, *contagion*, *convergence*, *coordination*, *entrainment*, *mimicry*, *mirroring*, *synchrony*, and *synergy*. Of course, this is by no means an exhaustive list of possible terms describing interpersonal similarity. We chose to focus on these terms based upon their prevalence and/or claims of specialized (typically theory-specific) definitions.

The present study has two main goals. First, we seek to identify possible groupings of terms. By relying on metascientific analysis techniques, we can look within the data to find the most salient dimensions along which to divide the data. If the meaning of these terms are distinct and well-defined, automatically identified clusters within the data should fall along such differences. If these terms are somewhat less important to the core ideas within the research area, we should find groups emerge along other lines (e.g., specific domains of cognitive science).

Second, we hope to identify one or more term(s) that could be used in a more general fashion based on their current usage patterns. Although the use of more specialized terms be useful in signaling specific concepts, providing a single term as a catch-all "umbrella" term may be useful for researchers when discussing their works or choosing publication keywords. We do not claim that this will be a panacea for this important problem within the field. However, identifying a single umbrella term that can be used by all researchers—in addition to any more specific keywords—may provide a crucial tool for both producers and consumers of the research within this research area, especially while more granular definitions and relations can be identified.

Importantly, we recognize that analyses like these are not a substitute for critical thinking. Instead, we view them as important tools for conscious theory-building. We hope that the present work will provide additional momentum—and vital data—towards solving an important problem for this research area.

2.2 Materials

2.2.1 Corpus Creation and Preparation

We compiled a corpus of abstracts from scientific research on interpersonal similarity. Abstracts were scraped from Thomson Reuter's Web of Science (http://www.wokinfo.com/) with a series of searches for English-language abstracts within the "Psychology" subject field. Abstracts were automatically identified and scraped for analysis by performing separate searches for each of the following 11 phrases (with asterisks as wildcard characters): *interpersonal accommod**, *interpersonal adaptat**, *interpersonal alignm**, *interpersonal contagion*, *interpersonal converg**, *interpersonal coordin**, *interpersonal entrainmen**, *interpersonal mimic**, *interpersonal mirror**,

[3] One additional attempt (Butler, 2011) specifically targeted emotion temporal dynamics, not the field overall. This was also largely subjective and divided terms by the methods associated with each term.

*interpersonal synchron**, and *interpersonal synerg**. Duplicate records were then removed, and punctuation, digits, common stopwords[4], words with fewer than 3 characters, and words that appeared in fewer than 5 unique abstracts were removed from all abstracts.

After creating the initial corpus, we found that the *interpersonal adaptat** search made up nearly half of the data in the corpus. Upon closer examination of the data, we found that a large number of these abstracts targeted a different phenomenon than that under consideration in the current paper. Therefore, our final corpus excluded any abstracts that were obtained solely with that keywords search, although those that were also identified in other keyword searches were retained.

The final corpus comprised 2,540 unique abstracts in 668 unique publication sources. After cleaning the data (described above), the corpus included 234,721 total words and 4,969 unique words. A total of 5,903 unique authors were represented in the corpus[5], with an average of 3.31 authors per article. The corpus included 16,971 total keywords and 5,115 unique keywords. Publication dates ranged from 1991 to 2015.

While this sample size may not be as large as other scientometric analyses, the sample size is still quite large in the context of the current analysis. Much larger scientometric analyses that rely on tens of thousands of abstracts focus on science writ large (e.g., Griffiths & Steyvers, 2004) or on an entire branch of scientific research (e.g., Bergmann et al., accepted). By contrast, the current analyses use scientometric analyses to better understand a single, still relatively young offshoot of a branch of scientific research. This will necessarily lead to a smaller sample size, but the specificity and depth of the sample will facilitate finely tuned interpretation of these data.

2.2.2 Analyses

We utilized three types of natural language processing (NLP) analyses: *latent semantic analysis* (LSA), *latent Dirichlet allocation* (LDA), and a neural-networks deep learning approach. Together, these three approaches allowed us to look for robust, convergent trends within the data. Unlike other text analysis tools (e.g., Pennebaker, Booth, & Francis, 2007), these methods are not pre-programmed with word meanings, parsers, or dictionaries. Instead, these methods identify underlying structure within the data while remaining agnostic to the interpretation of the identified structures. Below, we briefly introduce each and provide additional resources for further detail.

Latent Semantic Analysis

Latent semantic analysis (LSA; Landauer, Foltz, & Laham, 1998) is a dimensionality reduction tool often used to find underlying concepts across texts. LSA determines the meanings of words through their co-occurrence with other words across various, allowing LSA to identify similarities based solely on the target corpus by comparing how each word and text "loads" on various dimensions. These dimensions are neither labeled nor interpreted by LSA: LSA simply pulls apart the data. Users are free to interpret individual dimensions or to simply use the loadings across all dimensions for words or texts. Similarity is calculated as the cosine of the target vectors representing the target word or text, and the resulting value serves as a correlation in the targeted n-dimensional space. All LSA models in the present analyses rely on 300-dimensional spaces (cf. Landauer, McNamara, Dennis, & Kintsch, 2013).

[4]Using the English `stopwords` list from the `nltk` Python module (Bird, Klein, & Loper, 2009). We expanded this list to include the following lexical items: *across*, *also*, *among*, *beside*, *may*, *however*, *within*, *yet*, and longhand numbers *zero* through *ten*.

[5]A total of 4,723 unique author surnames were included.

Latent Dirichlet Allocation

Latent Dirichlet allocation (LDA) is a generative probabilistic topic modelling technique that allows users to identify underlying topics within a given corpus (e.g., Blei, Ng, & Jordan, 2003; Griffiths & Steyvers, 2004). Essentially, LDA interprets lexical items by estimating the probabilistic distribution of underlying concepts that make up each document (i.e., in our case, each abstract).[6] LDA identifies underlying structure within the corpus but does not attempt to label the emerging topics for the user. We implement LDA using the `topicmodels` package (Grün & Hornik, 2011) package in R (R Development Core Team, 2008). Additional information on the specific LDA model is provided in the Results section.

Deep Learning Methods

Deep learning (DL) is a class of machine learning techniques that takes a neural networks approach to unsupervised classification. We implement deep learning over our corpus with `gensim`'s (Řehůřek & Sojka, 2010) `word2vec` algorithm, a Python-based instantiation of recent work by Mikolov and colleagues (Mikolov, Chen, Corrado, & Dean, 2013; Mikolov, Sutskever, Chen, Corrado, & Dean, 2013). The method essentially creates a probabilisitic representation of the relations between words within a given space through a "skip-gram" approach to estimating that space. Rather than relying on existing semantic models (e.g., Google News; Mikolov, Chen, et al., 2013; Mikolov, Sutskever, et al., 2013), we created novel semantic models using our corpus of abstracts. This ensures that all results will speak strictly to related scientific uses of these words within this research area.

2.3 Results

2.3.1 Keyword Analysis with LSA

As a first-pass analysis, we explored patterns of author-generated keywords. This provides a glimpse into authors' self-identification with these different terms as a sort of proxy for a more explicit probing of experts' understanding of the relation between the terms. We chose to rely solely on LSA (rather than including LDA or DL) to analyze the author-generated keywords, given the relatively small amount of these data. We modeled the author-generated keyword data in a unique 300-dimensional space built from all author-generated keywords for each abstract included in the final corpus. Multi-word keywords were treated as distinct units to retain intended author meaning.

These connections are visualized in Figure 2.1, which features the strongest positive and negative connections in this network (see legend). Interestingly, no strong negative connections emerge between the terms in this network. All terms are either too weakly related to be included in the graph or are positively related to one another. Surprisingly, *synchrony*—one of the oldest and most widely used terms—appears in only 46 abstracts and is not strongly connected to any other term, although related term *entrainment* is.

Coordination emerges as a relatively diffuse term within this network. *Coordination*—including more specific variants of coordination (i.e., *unintentional interpersonal coordination* and *bimanual coordination*)—is densely connected both to other key terms and to other top keywords. However, these author-generated keywords are

[6]For an excellent conceptual introduction to probabilistic topic modeling—including LDA—see Blei (2012).

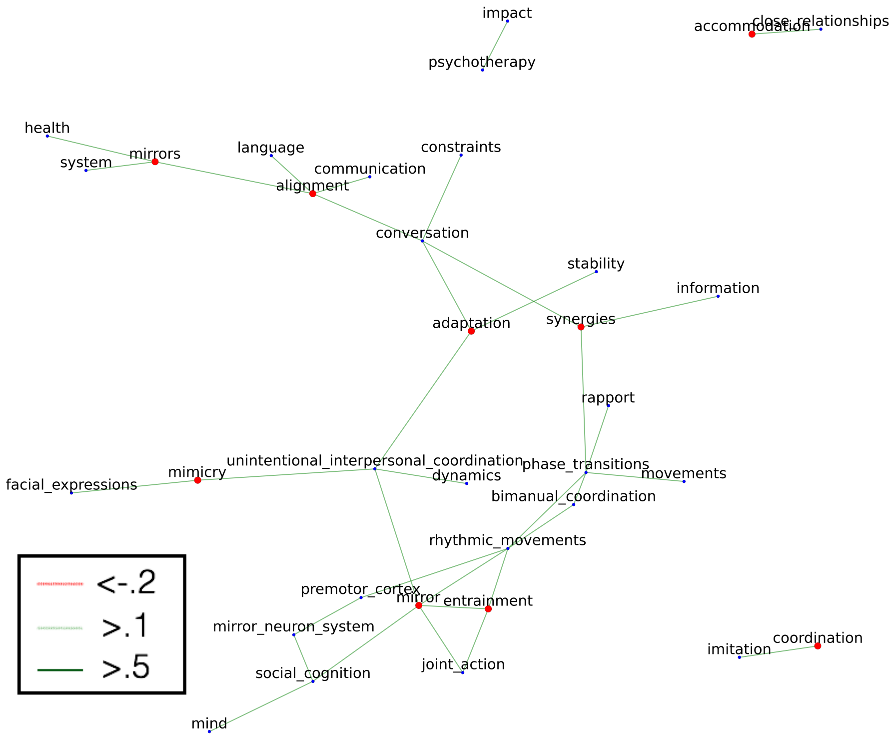

Figure 2.1: Network of top author-generated keywords in corpus. Each node is a single keyword, and connections are determined by the cosine similarity scores (in the 300-dimension keyword LSA space) between two nodes. Multi-word keywords are graphed with an underscore between each word. Keywords with red nodes are (unigram) key terms under consideration in this paper. Connections are drawn according to strength (see legend).

not strongly related to one another, further supporting the idea of a more distributed meaning of the term.

Several small clusters emerge from these data. For example, a cluster of movement-related keywords is most closely linked with key terms *mirror*, *synergies*, and *entrainment*. Interestingly, we also see *mirror* on the fringe of a cluster of neuroscience-related terms (cf. Calvo-Merino et al., 2005). *Alignment* is linked to words related to conversation, which is consistent with its beginning in language contexts (Pickering & Garrod, 2004). *Synergies*—arguably one of the newest terms in this area—bridges these two groups and is related to both language (cf. Fusaroli et al., 2012) and movement (cf. Riley et al., 2011).

We also see relationships between key terms, either linked directly or by one intervening word. For example, *entrainment* and *mirror* are directly positively linked, and both are further linked to *joint action*. *Mirrors* and *alignment* are also directly linked, although they share no other strong connections. *Alignment* and *synergies* are linked via *conversation*, while three key terms—*adaptation*, *mimicry*, and *mirror*—are all directly connected to *unintentional interpersonal coordination*.

Taken together, the results from the keyword analysis support the idea that these terms may not be strongly distinct from one another but may still belong to fuzzy domains. Some terms may be competing for the same conceptual territory, as demonstrated by their common links. At the same time, clusters of author-generated keywords—including key terms—appear to emerge along the domain of study (e.g., language, movement, neuroscience).

It is important to emphasize that we cannot say that these terms are synonyms simply because LSA identifies a positive relation between them. LSA is notoriously unable to differentiate between synonyms and antonyms, as patterns of co-occurrence between antonyms are often similar to patterns of co-occurrence between synonyms (Landauer et al., 1998). For this reason, we simply use LSA to highlight whether these key terms are perhaps vying for similar spaces—regardless of whether their interpretations of those spaces are compatible with one another.

Again, this keyword analysis offers a glimpse at the more explicit level of categorization of these terms: Authors are self-identifying their works as belonging to one or more of these camps. As a result, the patterns of relationships that occur between these terms may be somewhat biased by the authors' own conceptualizations of the terminological landscape. The following analyses address this by moving away from author-generated keywords to examine more implicit relations that underlie authors' abstracts.

2.3.2 Abstract Analysis with LDA

Unexpectedly, we found that the probabilistic topic space was not particularly well-separated in our initial explorations. Initial models were highly unstable, with model-over-model topic stability (with new random seeds) as low as 30% for some topics. As a result, we systematically compared (1) data cleaning and preparation techniques and (2) LDA model parameters to create the most stable topic models possible.

The data processing and preparation procedures described in the Method section were chosen based on their ability to yield the most stable LDA model. Consistent with prior work and recommendations (Griffiths & Steyvers, 2004; Grün & Hornik, 2011), the model used Gibbs sampling, a fixed prior (β) of 0.1, and a constant α of $50/T$. After comparing models with various T, we selected a model with 10 topics, maximizing model-over-model topic stability while also accounting for human interpretability (cf. Chang, Boyd-Graber, Wang, Gerrish, & Blei, 2009) and topic coherence.

The top 10 words for each topic in the model are presented in Table 2.1, along with our label for each topic. Figure 2.2 projects the topics into a two-dimensional space. Based on the distribution of the topics and words in each, we interpret the x-axis (PC1) as an individual-level/population-level (negative x-positive x) dimension and the y-axis (PC2) as a personal/abstract (negative y-positive y) dimension. The numbering of these topics is not indicative of any rank ordering and is simply for identification. As noted above each list in Table 2.1, the broad topics are persistent across runs, although individual lexical items are somewhat less stable.

The most striking result from the LDA model is the nature of the topics. The most salient dimensions of the corpus—as identified by this probabilisitic model—lie in the *broad research areas* and modalities, not *specific terms*. The rich diversity of the research areas identified in the topics is reassuring on a conceptual level, given the impression of interdisciplinarity of this field. By contrast, if the terms used to describe the phenomenon were the most important lines of division for the corpus, we would expect to see these topics emerge with strong connection to specific terms. This is especially important to note given that the corpus itself was generated using searches with these terms across the entire field of psychology, *not* research questions.

These results broadly support findings from the author-generated keyword model. In the author-generated keyword model, we found clusters emerging around research topics rather than specific terms, with multiple terms sometimes occurring in

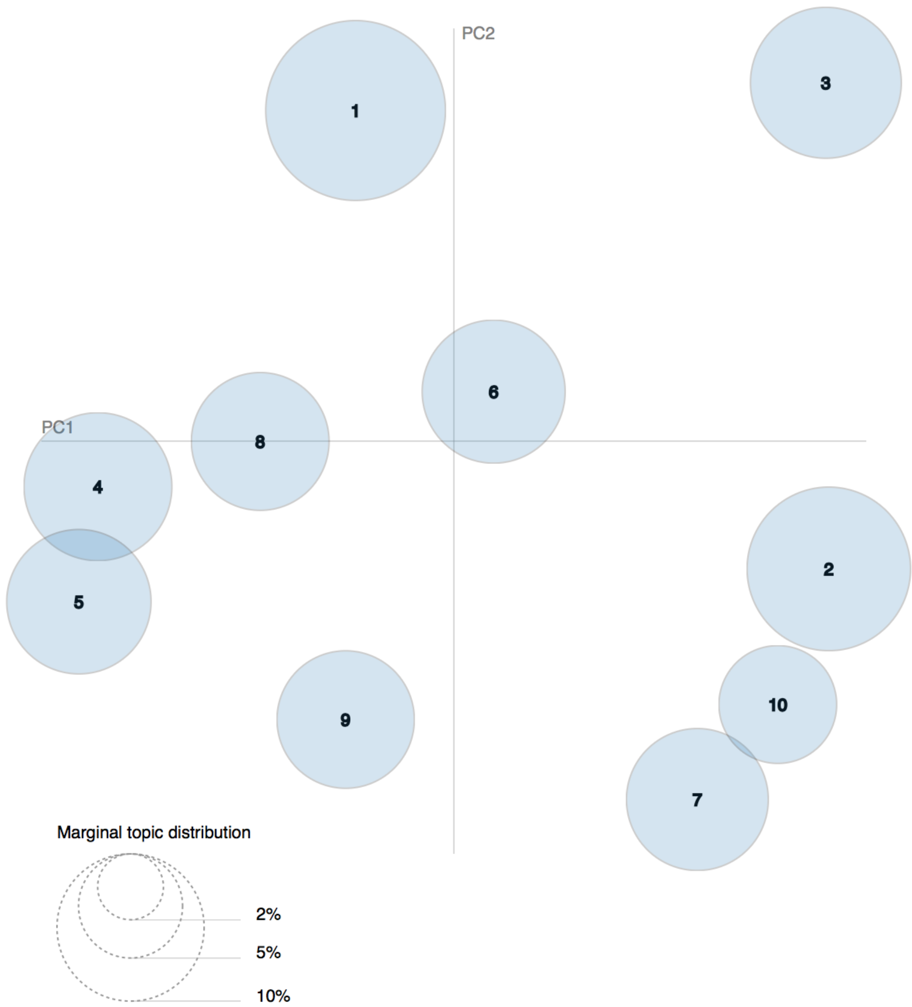

Figure 2.2: Projection of multidimensional LDA topic distribution onto two-dimensional space. The top 10 lexical items in each topic may be found in Table 2.1 under the appropriately numbered topic. This visualization was created in R (R Development Core Team, 2008) with `LDAvis` package (Sievert & Shirley, 2014), using an LDA model implemented in the `topicmodels` package (Grün & Hornik, 2011).

a single cluster. Results from the LDA model—constructed with a much larger and richer dataset—are similarly structured. Interestingly, we find several parallels to the LDA topics in some clusters from the keyword model, including clusters around neuroscience and movement dynamics (see Figure 2.1), highlighting the robust nature of these differences.

2.3.3 Abstract Analysis with LSA

We modeled the abstract data with LSA in a new 300-dimensional space (i.e., not the author-generated keyword space). We first visualized the relations exclusively between the key term groups in a network. To do so, we extracted the high-dimensional vectors for all words in each key term group (e.g., for *alignment*: *align*, *aligns*, *aligning*, *aligned*, *alignment*). We computed pairwise similarity scores for all possible pairs of these key terms within the abstract corpus as cosines in the high-dimensional space. The resulting network allows us to investigate just the relations among the key terms (see Figure 2.3).

The visualization provides some preliminary insights into term relations in this space. As with the author-generated keyword space, we again see some clusters emerge with multiple key terms, although restricting the visualization to include only key terms strips the broader context (e.g., intervening relations). At the same time, the larger semantic space provides the opportunity to see new comparisons within each key term group. From this, we see some key term groups with diffuse meanings across the constituent terms (e.g., *synchrony* and *adaptation* words), while other terms have very exclusively (or nearly exclusively) interconnected networks (e.g., *mimicry* and *synergy*).

Next, we compared the neighborhood density of the key terms by identifying the top 20 connections for each overarching group of key terms. To determine whether these terms are used in reliably different ways, we performed a one-way ANOVA over the cosine distances for the top 20 connections across the 11 key term groups. Results of the model highlight significant differences in the neighborhood densities of each group [$F(10, 209) = 82.36$, $p < .00001$]. This suggests that these terms are not used uniformly: Instead, these terms differ in their neighborhood density, which can be interpreted as a sign of specificity or interrelatedness.

A post-hoc pairwise Tukey test showed reliable patterns of variation across the term groups. For example, *synergies* demonstrated the most tightly connected neighborhood of the terms, and *contagion* appears to be the most weakly connected to its 20 closest neighbors. Interestingly, the mean neighbor cosines values for many of these terms are below .5, suggesting only a moderate relationship among their closest neighbors (e.g., *convergence*, *alignment*, *coordination*, and *synchrony*). These weak-to-moderate results may suggest that the patterns of use of these key terms are not characteristic or unique enough to create strong connections to their closest neighbors.

2.3.4 Abstract Analysis with Deep Learning

Deep learning (DL) is a useful addition to these analyses given its reliable detection of relationships between words, even in relatively sparse data (e.g., Mikolov, Sutskever, et al., 2013). Therefore, we complement our frequentist analysis of the space (LSA) using a neural-networks approach to estimating the same space. This allows us to explore subtler relations among the terms that may be not appear frequently enough to be detected by LSA.

As with LSA, `word2vec`—the specific DL method used here—encodes meaning of a single word as a high-dimensional vector within a given semantic space. We generated a probabilistic semantic space using the abstract data and extracted vectors

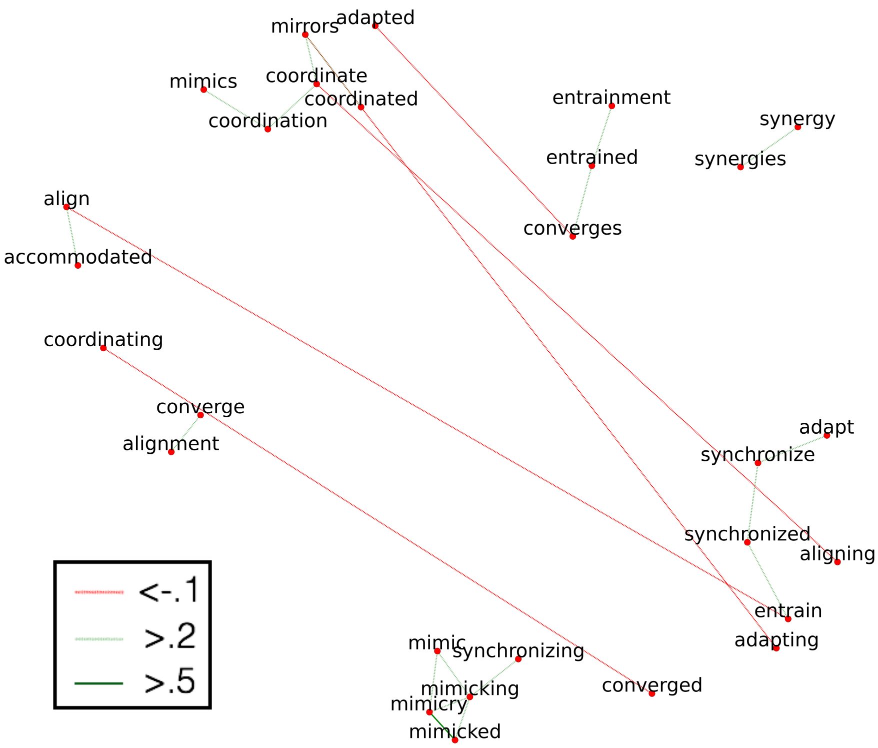

Figure 2.3: Network of LSA-identified relations across key terms in abstract corpus. Each node is a single term from a key term group, and connections are determined by the cosine similarity scores (in the 300-dimension abstract LSA space) between two nodes. Connections are drawn according to strength (see legend).

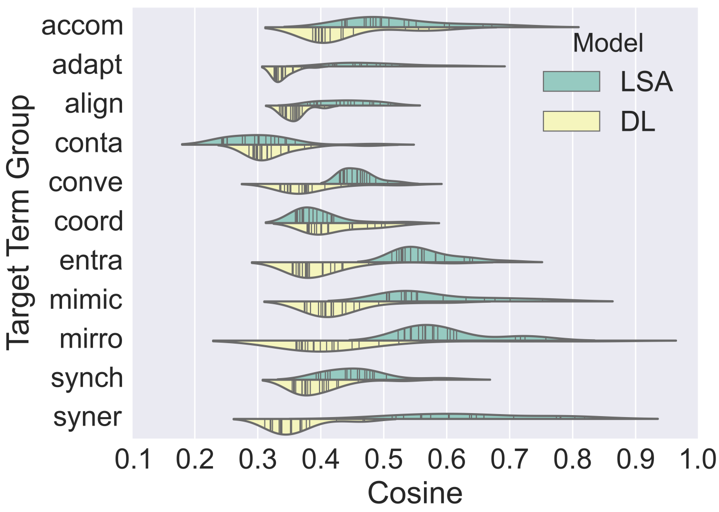

Figure 2.4: Distribution of neighborhood densities of each group of terms generated by LSA and deep learning (DL) methods. Term groups (on y-axis) are presented as stems, and the strength of the relationship between its 20 nearest neighbors are charted along the x-axis. Neighborhoods generated by LSA (in green) and DL (in yellow) are presented side-by-side for each group. Lines inside each "violin" are a single cosine value within the 20 nearest neighbors from each method. Created in Python with the `seaborn` package (Waskom et al., 2015).

for each word in the corpus. We then identified the nearest neighbors for each of the 11 key term groups as the 20 most strongly related words (identified by highest cosine value between high-dimensional vectors) to any word within the group.

To determine whether there were any differences in neighborhood densities identified with DL, we performed one-way ANOVA over the neighborhoods of each key term group. Term group significantly predicted cosine strength of the 20 nearest neighbors [F(10, 209) = 9.95, p <.00001] (see Figure 2.4). Consistent with the LSA neighborhood results, this suggests that there are reliable differences in neighborhood characteristics for each of these key terms in the DL model.

A post-hoc pairwise Tukey analysis of this ANOVA again revealed interesting patterns in the data, although not entirely consistent with the LSA results. Notably, the cosine values appeared to much lower for all terms in the DL model. Given these differences, we compared the neighborhoods of the key terms generated by LSA and DL. A paired-samples t-test of the key term neighborhoods found a significant difference in the neighborhood densities for the two models, $t(219) = 16.58$, p <.0001. A supporting 2 (model) by 11 (key term group) ANOVA found a significant effect of model [F(1, 418) = 470.19, p <.0001], key term group [F(10, 418) = 53.30, p <.0001], and the interaction term [F(10, 418) = 24.64, p <.0001].

A follow-up Tukey comparison of means found that nearly half of the terms—*adaptation*, *alignment*, *entrain*, *mimicry*, *mirror*, and *synergy*—showed significantly denser LSA neighborhoods than DL neighborhoods (all ps <.0001). Results from the other half of the terms did not significantly differ between the two models (i.e., *accommodation*, *contagion*, *convergence*, *coordination*, and *synchrony*). The differences between the two models, then, were largely driven by terms that are proposed (by some) to have specific theoretical connotations. This supports the idea that researchers may be attempting to use these terms in specialized ways—even though the underlying meanings of the terms are less well-specified.

2.4 Discussion

Work from a large and growing research area has sought to answer why and how people become more similar. From affective dynamics to motor control, numerous important empirical findings have been presented under a number of different terms. This increased attention has led to an improved understanding of the phenomenon, but it has not yet led to a unified terminology that could facilitate conversation across the research community. The present research has provided the first quantitative attempt to clarify this terminological confusion through a data-driven exploration of the literature surrounding 11 terms: *accommodation*, *adaptation*, *alignment*, *coordination*, *contagion*, *convergence*, *entrainment*, *mimicry*, *mirroring*, *synchrony*, and *synergy*.

We incorporated multiple analyses for a converging understanding of the field, combining frequentist (i.e., latent semantic analysis or LSA), probabilistic (i.e., latent Dirichlet allocation or LDA) and neural networks (i.e., deep learning or DL) perspectives. Although we have found a number of interesting patterns within the data, we set out in our analyses to identify (1) underlying dimensions for meaningful clusters in the data and (2) a term that could be used as a broad indicator of the phenomenon. We summarize the most relevant points to each of these two goals below.

2.4.1 Specialization: Research Questions, not Terms

Different authors present different perspectives on the terminology of interpersonal similarity, often with conflicting ideas on the specific meanings denoted by each term. One perspective is that these terms may represent various theoretical stances. To test this idea, we used LSA and LDA to extract the most cohesive groups from the data. Our results from these complementary analyses suggest that the research domain of the similarity is a much more salient grouping of the data than the specific used to describe that similarity. From analyzing patterns of author-generated keywords to automatic topic identification, we consistently find that the abstracts separate by area of study or type of question, not term.

2.4.2 Broad Usage: Coordination

Even while some authors insist that there are strong delineations between these terms, others treat the terms interchangeably. Still others want to employ broad "umbrella" terms that can simply identify the phenomena without implying any specific theoretical stance. To investigate whether any terms in the literature could be suitable candidates to fill such a role, we explored the connectedness of the semantic spaces for the terms. From these analyses, we identified *coordination* and *synchrony* as two possibilities.

Converging evidence from three analyses—LSA over author-generated keywords, LSA over abstract text, and DL over abstract text—support intuitions that *coordination* is a broad term with diffuse meaning. Model results from author-generated keywords show that *coordination* and similar words act as "hub" terms, with numerous moderate connections to many other keywords (including other key terms) but no strong connections to one another. Analyses of the abstract text show *coordination* has a more diffuse definition in high-dimensional space—not the tightly knit neighborhoods that we would expect to see with a very specialized term.

We find some similar results for the term *synchrony*, though not entirely identical. Interestingly, the term is surprisingly underrepresented in the author-generated keywords in the corpus did not appear in the network generated by that semantic space, so we can only draw conclusions from its appearance in the abstract LSA and DL models. Post-hoc tests of these analyses find no significant difference in the distributions of *synchrony* and *coordination* in the DL model (p = .33), although *synchrony* is significantly more specialized than *coordination* in the LSA model (p <.001). These conflicting results are interesting given the neighborhood densities (or level of specialization) for each term separately do not significantly differ between DL and LSA models. This may suggest that *synchrony* is approaching the broad use of *coordination* but with a slightly more specialized use.

Taken together, our findings suggest that *coordination* may be able to serve as the umbrella term we sought to identify. Based on its current levels of prevalence, diffuse meaning, and frequent interconnectedness to other key terms, *coordination* could easily be adopted as a broad term to denote the phenomenon without taking a stance on theoretical issues. Similar patterns of usage suggest that *synchrony*—one of the oldest terms in this field—could fill a similar function, but interesting differences between the two require further exploration.

2.4.3 Limitations and Future Directions

While an important first step towards a solution, this work can only be *part* of the solution. Much additional work—including further qualitative (cf. Butler, 2011; Delaherche et al., 2012) and quantitative analyses—should be done to help resolve this issue. From the quantitative perspective undertaken in the present analyses, the current work has several limitations that serve as opportunities for future direction.

First, the underlying reason for this consistency across different models has not been addressed here. These terms may be strongly linked to different research areas because the authors are approaching the question from a particular background in cognitive science (e.g., developmental psychology, neuroscience, social psychology) with unique terminological trends. (For example, are similar body movements labeled as *accommodation* by linguists and as *mirroring* by neuroscientsts?) On the other hand, it could be that the modality under consideration (e.g., affect, language, movement)—regardless of the author's specific discipline—is the primary driver of these term groups. (For example, do both linguists and neuroscientists talk about similar body movement as *synchrony* but similar affect as *contagion*?) Understanding the reason for these differences may help come to a better resolution to the current problem.

Second, the use of abstracts instead of entire works may wash out nuances across the terms and categories. The 100-word abstract may force researchers to choose more common terms over their preferred terms in order to communicate with a wider audience, or the limited space may instead force researchers to focus simply on their theoretical view rather than relating it to other theoretical stances. Future work may compare model results using abstracts only with model results from using entire articles.

Third, the current efforts could be expanded to include other terms. While we have chosen 11 prevalent and/or theory-related terms for the current analysis, other terms also exist within the research area (e.g., *coupling*, *imitation*). Future work could expand the scope of these analyses to include these additional terms—and perhaps to create a comprehensive list of all terms.

Finally, we understand that these articles are situated within a much broader (and often highly interdisciplinary) context. We restricted ourselves only to articles within this very specific domain of interpersonal similarity in order to get a fine-grained picture of the field, but understanding the terms' relation to the larger literature would be incredibly valuable as well. By looking only at the fine-grained trends, we may be missing valuable data that could shed light on how (and why) these different terms are used.

2.4.4 Conclusion

The study of interpersonal similarity and related behaviors helps us understand a vital part of human social behavior. However, this research area is currently plagued by scattered terminology with little consensus on how these terms fit together. We turn metascientific methods into a tool for conscious theory-building that can help resolve an important issue within this research area. We present data-driven explorations of the field that highlight the importance of the research topic—not terminology—in defining our research area. After exploring 11 of the most common terms, we propose that *coordination* could be used as a theory-neutral umbrella term to describe the phenomenon as the field continues to define itself, its phenomenon, and its terminology.

Table 2.1: Top 10 words included in each topic from LDA analysis over abstracts, ranked descending by weight. Each topic's model-over-model stability—as a percentage of 10 runs—is included in parentheses under its name. Topic labels included in quotations under model-over-model stability.

Topic 1 (100%) *"social theory"*	**Topic 2** (100%) *"psychometrics"*	**Topic 3** (100%) *"health"*	**Topic 4** (100%) *"movement dynamics"*	**Topic 5** (100%) *"interpersonal communication"*
social	validity	health	coordination	synchrony
research	scale	patients	interpersonal	interaction
processes	factor	treatment	phase	participants
interpersonal	interpersonal	care	movements	task
cognitive	convergent	patient	task	coordination
theory	personality	study	participants	behavior
perspective	measures	family	time	movement
model	measure	data	performance	joint
understanding	self	support	results	social

Topic 6 (90%) *"groups and teams"*	**Topic 7** (80%) *"romantic relationships"*	**Topic 8** (100%) *"neuroscience"*	**Topic 9** (90%) *"affect"*	**Topic 10** (100%) *"developmental"*
group	relationship	social	emotional	children
social	self	brain	social	social
study	women	mirror	participants	age
groups	study	system	self	child
communication	relationships	neural	interpersonal	peer
team	partner	actions	facial	behavior
results	interpersonal	empathy	mimicry	school
performance	sexual	action	emotions	development
trust	men	activity	study	infants
members	sex	cortex	people	early

Chapter 3

PsyGlass: Capitalizing on Google Glass for naturalistic data collection

Cognitive and social scientists often efficiently leverage commercial technologies to enhance behavioral measurements in experimental paradigms. For example, the ubiquity of the personal computer permits easy computer-mouse tracking, allowing researchers to investigate the continuous dynamics of cognition and decision-making over time by charting mouse-movement trajectories during computer-based experiments (e.g., Freeman & Ambady, 2010; Huette & McMurray, 2010; Spivey & Dale, 2006). As video game consoles opened their platforms to developers, researchers have targeted the Nintendo Wii and Microsoft Kinect as opportunities for new behavioral tracking techniques. The Nintendo Wii became an extension of the mouse-tracking paradigm, allowing researchers to track free arm movements during choice selection (e.g., Dale, Roche, Snyder, & McCall, 2008; Duran, Dale, & McNamara, 2010), and the Microsoft Kinect provided highly affordable motion-tracking of overall body movements and specific effectors (e.g., Alexiadis et al., 2011; R. A. Clark et al., 2012; Oikonomidis, Kyriazis, & Argyros, 2011). Increasing computer availability and online presence has brought opportunities for worldwide data collection through services such as Amazon Mechanical Turk (e.g., Crump, McDonnell, & Gureckis, 2013; Paolacci, Chandler, & Ipeirotis, 2010). The recent explosion of open mobile application ("app") development has provided researchers with the opportunity to integrate mobile phone technology into studies in and out of the lab (e.g., Gaggioli et al., 2013; Henze, Pielot, Poppinga, Schinke, & Boll, 2011; Miller, 2012; Raento, Oulasvirta, & Eagle, 2009). These are, naturally, just a handful of examples among many adaptations of technology for research purposes.

Over the past decade, a new breed of technology has emerged and is poised to generate new experimental and methodological explorations. Numerous segments of the technology industry have moved into wearable technologies as a new avenue for products and services. From smart watches to fitness trackers, these devices offer a range of services with a variety of applications and intended audiences that can be integrated into behavioral applications (e.g., Goodwin, Velicer, & Intille, 2008; Klonoff, 2014; Picard & Healey, 1997; Starner et al., 1997). One well-known wearable technology is Google Glass (Google, Inc.), a multipurpose device worn on the face like glasses (see Fig. 3.1). Its range of functionalities and its openness to developers make it a potentially powerful tool for cognitive and social science research, both in and out of the lab.

Through research-based apps, Google Glass can provide researchers with real-

Figure 3.1: Photo of Google Glass (Google, Inc.: www.google.com/glass)

time control of even very subtle stimuli while unobtrusively tracking various behavioral measures. Glass can present wearers with visual stimuli on a small screen just over the right eye and with audio stimuli through a bone conduction transducer or proprietary earbuds. Wearers navigate Glass through voice command and with a small touchpad over the right temple. The device can capture high-resolution videos and photos, and researchers can track wearers' head movements with on-board three-axis gyroscope and accelerometer sensors. Glass also includes on-board memory, wireless capabilities, and Google's Android mobile operating system.[1]

Here, we first briefly review prior work that has used wearable technologies broadly and Glass specifically. We then introduce PsyGlass, our open-source platform for incorporating Glass into behavioral research that taps into some of these capabilities for naturalistic experimental work. As an example application for developing experimental paradigms with PsyGlass, we present a simple behavioral experiment that uses Glass both to present visual stimuli to participants and track participants' movements during a naturalistic interaction task. We end with a list of recommendations for using PsyGlass, our goals for expanding its capabilities, and a brief discussion of how wearable technology can contribute to behavioral research.

[1]This information is current as of December 2014 and describes the Glass Explorer model (version 2). Detailed specifications are freely available through Google Developer's Glass resources (http://developers.google.com/glass).

3.1 Research opportunities for wearable technologies

Wearable technologies can give researchers the opportunity to track and quantify behavior in new ways. As technology has miniaturized while becoming more powerful, cognitive and social scientists have already begun looking for ways to incorporate it into research paradigms (e.g., Goodwin et al., 2008). Wearable technology is still a relatively underutilized methodology, but a growing number of researchers have adopted it in some behavioral and health-related domains. Although some of the capabilities provided by other wearable technologies may not be possible to implement with Glass, we here provide a brief history of wearable technology research, to establish wearables' existing foundation in research and to spark ideas for the kinds of questions to which Glass (and PsyGlass) could be applied.

3.1.1 Previous research with wearable technology

Interest in wearable technology in research-related settings has existed for quite some time. However, until recent advances in developer-friendly commercial technology such as Google Glass, many researchers have had to engineer their own wearable solutions. For instance, affective researchers have been engineering wearable solutions to track and classify affect for nearly two decades (e.g., Lee & Kwon, 2010; Picard & Healey, 1997). Since then, wearable technology has spread to other domains–most notably, to the health sciences (e.g., Moens et al., 2014; Moens, van Noorden, & Leman, 2010; for a review, see Pantelopoulos & Bourbakis, 2008).

One of the most prominent examples of wearable technologies in the behavioral sciences to date has been the sociometric badge, developed to provide a host of metrics on individual and group behaviors (e.g., Lepri et al., 2012; Olguín Olguín, Gloor, & Pentland, 2009; Olguín Olguín, Waber, et al., 2009; Pentland, 2010; Waber et al., 2011). The sociometric badge has been applied most heavily in analyses of workplace behavior and interactions (e.g., for describing a research network in Lepri et al., 2012; or in a hospital in Olguín Olguín, Gloor, & Pentland, 2009), exploring connections between workplace activities and social factors in largely observational-style studies. For more on sociometric badges and related work, see the review articles by Olguín Olguín, Waber, et al. (2009) and Waber et al. (2011).

3.1.2 Existing work utilizing Google Glass

Over the past year, there has been growing excitement about applying Glass in research, although the majority of published scientific work to date comprises commentaries. To the authors' knowledge, Glass has been featured in only one published experimental study in the behavioral sciences (Ishimaru et al., 2014). However, interest in Glass has surged in other research areas, especially the health sciences.

The health sciences are arguably one of the areas most interested in Glass, particularly as assistive tools. Recent commentaries have touted possible uses for Glass in laboratories (Chai et al., 2014; Parviz, 2014) or as assistive devices (Hernandez & Picard, 2014). From surgical assistance (Armstrong, Rankin, Giovinco, Mills, & Matsuoka, 2014) to dietary tracking (Mauerhoefer, Kawelke, Poliakov, Olivier, & Foster, 2014) to perceptions of health-related Glass use (McNaney et al., 2014), many preliminary integrations of Glass into the medical and health sciences have capitalized solely on existing Glass capabilities without additional app development. Only a handful of researchers have developed specialized apps with a variety of health science applications, such as facilitating food shopping (Wall, Ray, Pathak, & Lin, 2014), augmenting conversation for individuals with visual impairment (Anam, Alam, & Yeasin, 2014a, 2014b), and assisting biomedical technicians (Feng et al., 2014).

Other research areas have also begun to incorporate Glass, albeit to a lesser extent than in the health sciences. To the authors' knowledge, only Ishimaru et al. (2014) have incorporated Glass into cognitive science,[2] investigating how blink patterns and head movements can be used to categorize wearers' everyday activities. In the domain of human-computer interaction, He, Chaparro, and Haskins (2014) have developed a Glass app called "USee" that can be used to facilitate usability testing, providing separate components for participants, researchers, and other observers.

Despite this rising interest, the programming requirements for developing Glass apps could pose a significant barrier to entry for many cognitive and social scientists. Our goal is to lower this barrier by providing a framework for incorporating Glass that can be adjusted to individual research needs. By opening the application to community development, we hope to promote the important ethos of shared resources and to encourage others to grow the application with us.

3.2 PsyGlass: A framework for Glass in behavioral research

Google Glass provides behavioral, cognitive, and social scientists with many methodological and measurement possibilities as a research tool. Glass can simultaneously present stimuli and track various behavioral metrics, all while remaining relatively unobtrusive, cost-effective, and portable. However, developing research apps for Glass currently requires researchers to develop projects entirely on their own. We believethat a centralized resource with functioning example code and guidance through the development process could make Glass more accessible to a wider scientific audience.

To that end, we have created PsyGlass, an open-source framework for incorporating Google Glass into cognitive and social science research. All code for the PsyGlass framework is freely available through GitHub (GitHub, Inc.: www.github.com), allowing the research community to use, expand, and refine the project. The code is jointly hosted by all three coauthors and can be found in the PsyGlass repository on GitHub (http://github.com/a-paxton/PsyGlass).

PsyGlass facilitates data collection and moment-to-moment experimenter control over stimuli on connected Glass devices. Currently, PsyGlass supports single-participant or dyadic research, although it can be adapted to include additional participants. The framework (see Fig. **??**) includes a Web-based experimenter console and specially designed Glassware (i.e., a Glass app) built using Android Studio (Google, Inc.; http://developer.android.com/sdk/). PsyGlass currently presents only visual data and collects only accelerometer data, although we are working to expand data collection and stimulus presentation to other modalities, as well (see the Future Directions section).

3.2.1 PsyGlass experimenter console

The experimenter console is a streamlined Web interface that allows the experimenter to manipulate connected Glass visual displays (see Fig. 3.3). The console provides separate controls for up to two Glass devices, allowing the experimenter to update text and the background color displayed to each. With relatively basic JavaScript capabilities, experimenters may modify the console as desired to provide more automated solutions for one or more connected devices (e.g., presenting colors or words from a list at random).

[2]Some of the cited works from the health sciences have had behavioral components, but such works are *primarily* focused on health and/or medical applications.

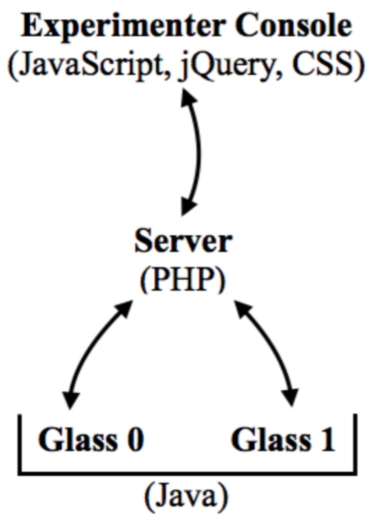

Figure 3.2: PsyGlass framework flow and the programming and/or markup languages of each component (listed in parentheses). In the experimenter console's current form, the researcher can use it to update visual displays on one or more connected Glass devices while collecting accelerometer data from each

The console also manages the connection between the server and the Glass. The experimenter can use the console to open the initial server connection for the Glass. Once all Glass devices are connected, the experimenter can initiate the data collection session simultaneously across all devices to ensure time-locked data collection and stimulus presentation. The console provides the experimenter with updates about each server-Glass connection (e.g., latency) while the Glass devices are connected to the server. Once data collection is finished, the console allows the researcher to end the data collection session (again, simultaneously across all connected devices) and close the server connection for both Glass devices.

3.2.2 PsyGlass Glassware

The PsyGlass Glassware allows the experimenter to update the visual display on the basis of stimuli sent from the experimenter console while recording three-dimensional accelerometer data. Once the server connection has been opened from the console, the wearer (or the experimenter) can initiate the server-to-Glass connection with the Glassware. After the console opens the data collection session, the Glassware regularly checks the server (by default at 4 Hz, or every 250 ms) to check for visual display updates issued from the console. Time-stamped x, y, z accelerometer sensor data are logged on a local text file every 4 ms (250 Hz, by default) until the data collection session has been ended.

After data collection has finished, the experimenter can upload the accelerometer data stored locally on the device to the server. Collecting and storing the data on the Glass helps prevent overheating of the device and preserves battery life, but data could be streamed continuously to the server with some changes to the PsyGlass framework. Data are saved to the server as a tab-delimited text file. To save space on the device, the previous session's data are deleted locally once a new data collection session is initiated. More information on the Glassware workflow is included in the Appendix.

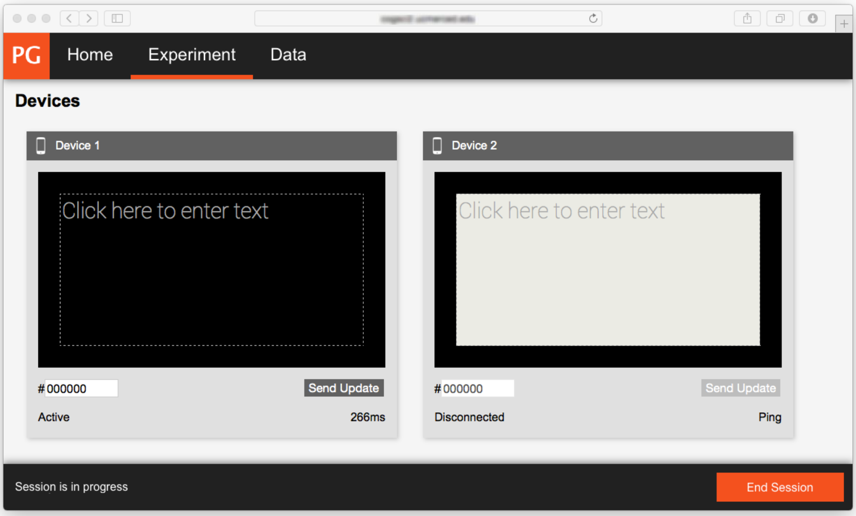

Figure 3.3: PsyGlass experimenter console. From here, the experimenter can manage the connection between the connected Google Glass device(s) and the server, initiate data collection sessions, and update the Glass screen(s) with text and/or color

3.2.3 Potential applications for PsyGlass

Although our initial interest in Glass grew from our studies of bodily synchrony during face-to-face dyadic interaction (Paxton & Dale, 2013a), it can be easily adapted for other settings. For example, researchers interested in humans' exploration of their environment might track movement while providing visual cues on the display, whereas a study on language production might introduce distractors or incongruent lexical items on participants' screens. In dyadic studies, researchers can use Glass to support naive confederate designs: A lexical cue or prearranged visual signal (e.g., color, shape) could serve as an instruction to lie to their partner during a conversation or to act confused while completing a map task. These are, of course, only a few brief examples, but they highlight one of the most compelling features of PsyGlass: targeted control over a participant's stimuli on the fly, even in highly naturalistic settings.

To demonstrate how PsyGlass can be used to facilitate behavioral research, we present data below from an experiment investigating how individuals compensate for distraction during conversation.[3] This preliminary study demonstrates how Glass may open opportunities for new experimental designs with distinct theoretical implications. We believe that Glass presents a unique opportunity for interpersonal behavioral research, given its commercial availability,[4] relative affordability, and array of sensing capabilities. The experimental design, data collection procedures, and data analysis provide a concrete example of how PsyGlass can be deployed to extend theory-rich questions into new domains.

[3]These data are part of a larger ongoing research project investigating how interaction is affected by various contextual pressures.

[4]The protocol for purchasing Google Glass has changed. Further information is provided in the General Discussion.

3.3 Example PsyGlass application: Convergence during interaction

Interpersonal convergence or synchrony broadly describes how individuals become increasingly similar over time while they interact (e.g., Shockley et al., 2009). Previous research suggests that one benefit of convergence may be to help individuals overcome impoverished communication signals. For instance, individuals' head movements synchronize more strongly during conversation with high ambient noise, as compared with conversation in an otherwise silent room (Boker, Rotondo, Xu, & King, 2002). These findings support the idea that interpersonal convergence may be vital to comprehension (e.g., D. C. Richardson & Dale, 2005; Shockley et al., 2009), perhaps by serving as a scaffold to support key aspects of the interaction in a synergistic account of interpersonal coordination (e.g., Riley et al., 2011; Fusaroli et al., 2012; Dale et al., 2014).

Building from Boker and colleagues' (2002) findings in the auditory domain, in the present study we tested whether low-level visual distractors—analogues to auditory distractors—increase interpersonal movement synchrony during friendly conversations. We compared participants' head movements during conversation (a) combined with a dual-task paradigm and (b) in the presence of "visual noise." Using PsyGlass, we were able to present visual stimuli separately to each participant while surreptitiously collecting high-resolution head movement data. We anticipated that dyads would synchronize more during the "noise" condition (cf. the auditory noise in Boker et al., 2002). We chose the dual-task condition as a comparison condition that could decrease interpersonal synchrony, given a constellation of previous findings (e.g., regarding working memory and synchrony in Miles et al., 2009; and working memory and dual-task paradigms in Phillips, Tunstall, & Channon, 2007).

3.3.1 Method

Setting up PsyGlass

Once our experiment was designed, we took a series of steps to set up the technical foundation for PsyGlass. As a dyadic interaction study, we prepared two Glass devices, one for each participant. First, the native Java code for PsyGlass must be compiled onto the Glass devices. The Java code distributed on GitHub (linked above) can be compiled in the Glass software development kit environment (called the "GDK"); Google's documentation for this process is quite thorough.[5] Second, to accompany PsyGlass on the Glass devices, we developed JavaScript code that controls the PsyGlass experimenter console. This JavaScript code (also included on GitHub) controls the nature and timing of the stimuli (described below). Third, we installed the PHP code on a server that coordinates data collection through the experimenter's browser in order to share the Glass devices' data with the server. Importantly, this setup requires that the experimenter's computer and the two Glass devices be connected to the Internet during the entire experiment.

Participants

In return for course credit, 30 undergraduate students from the University of California, Merced, participated as 15 volunteer dyads, none of whom reported knowing one another. Each dyad was randomly assigned to either the noise ($n = 7$) or the dual-task ($n = 8$) condition. Due to connectivity issues, one dyad's data (from the noise

[5] For a quick demonstration, see https://developers.google.com/glass/develop/gdk/quick-start.

condition) were removed from the present analyses, since fewer than 3 min of usable movement data were recorded. (See the notes about connectivity issues in the General Discussion.)

Materials and procedure

After completing several questionnaires (not analyzed here), the participants were seated facing one another in two stationary chairs approximately 3 feet 2 in. away from one another in a semi-enclosed space within a private room. Both chairs were seated in profile to a small table with an iMac 27-in. (Apple, Inc.) computer several yards away, from which the experimenter would run the PsyGlass experimenter console in the following experiment. Participants were then given 3 min to get acquainted without the experimenter present.

Once the experimenter returned, each participant was given a Google Glass with the PsyGlass Glassware and went through a brief setup process to become familiar with the device. The experimenter first described the Glass to the participants (i.e., explaining what the display and touchscreen were) and helped the participants properly fit the Glass to their faces. The experimenter then verbally guided participants through initializing the PsyGlass Glassware, providing the participants some experience with the device before beginning the experiment. The experimenter tested participants' ability to fully see the Glass by ostensibly checking its connection, using the PsyGlass experimenter console to present participants with either one word (i.e., "Glass" or "test") or color (i.e., red code #FF0000 or blue code #0000FF) and asking them to report what change they saw on their screen.

Crucially, all dyads were then told that their Glass display would switch between blue and red during the experiment. To implement this, we created a version of the PsyGlass experimenter console that updated the screen color once per second (1 Hz), with a .9 probability of a blue screen and a .1 probability of a red screen.[6] Dyads assigned to the dual-task condition were told to remember each time the screen turned red and that they would be asked to write down that number at the end of the conversation. This condition is akin to a dual-task oddball paradigm (Squires, Squires, & Hillyard, 1975). Dyads assigned to the noise condition were told that these switching colors were due to a bug in the programming and that they could ignore the changing screen during their conversation.

All dyads were then asked to hold an 8-min conversation with one another about popular media and entertainment (mean length = 8.12 min). After the remainder of the experiment,[7] participants were thanked and debriefed.

Analyses

Data were trimmed to exclude the calibration and instruction periods, retaining only the conversational data. The mean length of recorded movement data was 7.7 min (range = 4.17-8.86 min), largely due to connectivity errors in two of the included dyads. We converted the x, y, z accelerometer data for each participant into Euclidean distances to create a single metric of head movement over time, and then applied a second-order Butterworth filter to smooth the data. Cross-correlation coefficients (r) served as our metric of interpersonal synchrony, since they have been a fairly common metric for synchrony in previous research (e.g., D. C. Richardson, Dale, & Tomlinson, 2009). Cross-correlation provides a measure of the influence between individuals across windows of

[6] If the updated color was the same as the current color, the screen did not appear to change or flicker.

[7] Which included subsequent conditions not analyzed here, beyond the scope of the current demonstration.

time: By correlating individuals' time series at varying lags, we could measure the degree to which individuals were affecting one another more broadly. Following from previous research (Ramseyer & Tschacher, 2014), we calculated cross-correlation rs within a ± 2,000-ms window

3.3.2 Results

The data were analyzed primarily using a linear mixed-effects model. The random-effects structure (using random slopes and intercepts) was kept as maximal as possible (Baayen, Davidson, & Bates, 2008; Barr, Levy, Scheepers, & Tily, 2013). Dyad membership was included as the sole random effect. The condition was dummy-coded prior to inclusion (0 = *noise*,1= *dual-task*). All other variables—including interaction terms—were centered and standardized (Baayen et al., 2008) prior to being entered into the model.

This model served two purposes: (a) to replicate previous findings of *time-locked synchrony* of head movements during conversation (Ramseyer & Tschacher, 2014) and (b) to explore whether low-level visual distractors would negatively impact that synchrony relative to increased working memory load. The model predicted r—our measure of interpersonal synchrony or convergence—with lag (± 2,000 ms) and condition (dual-task = 1) as independent variables.

As anticipated, increases in lag significantly predicted decreases in r, providing evidence for in-phase interpersonal synchrony of head movements during conversation ($\beta = -.50$, p <.0001). The main effect of lag indicated that partners' head movements were most strongly correlated at lag 0—that is, in moment-to-moment comparisons. The correlation decreased as the time series were compared at increasingly disparate points.

However, contrary to our hypothesis, we found no significant difference between the noise and dual-task conditions ($\beta = .19$, p >.30), nor a significant effect of the interaction term ($\beta = -.03$, p >.60). In fact, the trend suggests that the *opposite* might be the case, with the dual-task condition being associated with *higher* cross-correlation coefficients (see Fig. 3.4). A two-sample t-test of the centered and standardized cross-correlation coefficients *only* at lag 0 showed a marginally significant increase in interpersonal synchrony during the dual-task condition, $t(13) = -2.1$, p <.06.

3.3.3 Discussion

In the present study, we explored how interpersonal dynamics during naturalistic conversation are affected by environmental factors. Inspired by previous work in the auditory domain (Boker et al., 2002), we investigated how visual distractors and increased working memory load differentially affect interpersonal synchrony by using PsyGlass to quantify head movements.

Although we replicated previous findings of head movement synchrony generally (Ramseyer & Tschacher, 2014), we found conflicting evidence for the impact of these conditions on synchrony. Although the longer-range convergence was not significantly different between the two conditions, moment-to-moment (i.e., in-phase) synchrony was marginally higher in the dual-task condition, contrary to our expectations. These unexpected results could have several implications for this literature, to be disentangled with follow-up work. First, the results could suggest that—although higher working memory load may increase lag-0 synchrony—convergence unfolds similarly over a longer timescale, regardless of the nature of the external visual stimuli.

Second, these findings could suggest a reframing of the conditions in the present study as compared with those used by Boker et al. (2002). Rather than interpreting the

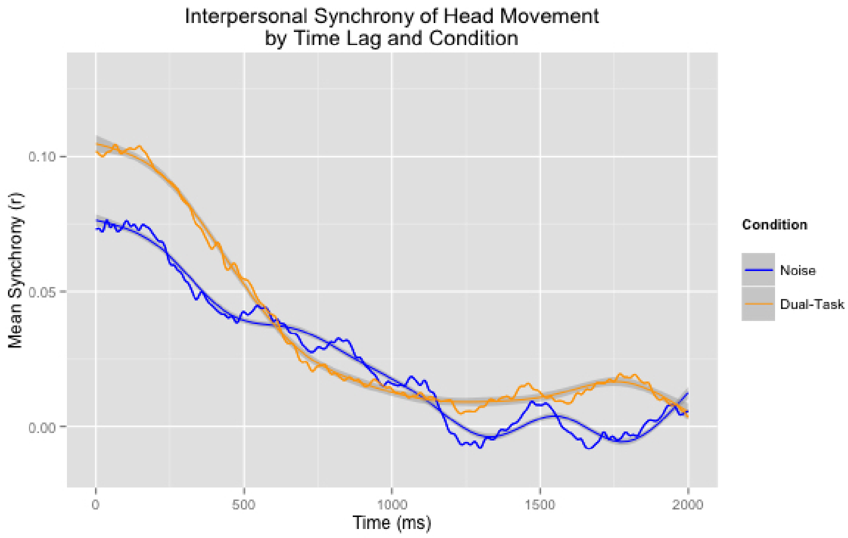

Figure 3.4: Interaction plot of the linear mixed-effects model for our sample application, predicting interpersonal synchrony (r: y-axis) as a function of condition (blue = noise, orange = dual task) across lags of ± 2,000 ms (x-axis).

auditory noise as a distractor, it might in fact have been more similar to the dual-task condition than the visual-noise condition: Both ambient noise and the dual task may be more task relevant and less easily ignored during conversation than the irregular blue-to-red screen switches. Perhaps the key element is that distractors should in some way be unavoidable during interaction.

3.4 Using PsyGlass: Recommendations and limitations

Below we compile a number of recommendations and limitations to consider when using Google Glass with PsyGlass. These items to consider should be useful for practical concerns about experimental design and data analysis with PsyGlass.

No prior Android experience is required, although it can be helpful. Prior experience with programming of some kind can be incredibly beneficial, especially in Java. However, resources for Glass, Android, Java, and JavaScript programming are widely available online through various online tutorials and forums. Note that compiling PsyGlass will require following the basic GDK instructions (see the Method section above).

Troubleshooting modifications to PsyGlass can take time, especially for those new to Android and Glass development. Those new to Android coding should first familiarize themselves with the basic PsyGlass program and start with incremental changes to the code, building to larger extensions. Numerous developer resources for Android and Glass are available through third-party sources (e.g., programming forums, tutorial websites) and Google Developers (Google, Inc.: https://developers.google.com/).

In its current form, PsyGlass is very battery-intensive. Researchers may consider reducing the computational strain (e.g., by reducing the sampling rate) if using the application for extended periods of time, to preserve battery life. In our example experiment, PsyGlass actively ran for a maximum of 20 min per data collection session.[8] By charging the Glass devices for up to 20 min between data collection sessions, we were able to run up to four back-to-back data collection sessions without battery problems. We imagine that this pattern could continue for longer but cannot say so from experience.

The on-board computer for Glass (which sits alongside the wearer's right temple) can become quite warm to the touch after extended intensive use or charging. Although a very small number of participants commented on this warmth, no participants reported it as being uncomfortable, even when the Glass had been in use or charging for up to 3 h before their data collection session.

Because the Glass display does not have an opaque backing, nearby parties may be able to see some of the stimuli presented on the Glass display. Bright colors are the most easily noticeable, being recognizable from farther away than 45 feet.[9] Although the presence of most text or shapes is perceivable from approximately 90 in., large text and shapes are somewhat identifiable as close as 21 in. and are distinctly readable by around 14 in. away. Small text, however, is unreadable even at 6 in. Researchers should take this into account and perform preliminary tests to ensure that it will not impinge on the experimental goals (e.g., during deception-based tasks). However, we have heard reports of others attaching lightweight backings to the Glass, which may serve as a solution in these cases.

Although Google Glass is designed to be worn over regular glasses, it can be somewhat difficult for some wearers to comfortably wear Glass while being able to easily see the entire screen. In some cases—like our color-based example study— being able to see most of the screen clearly should suffice. However, this may be an issue for experimental designs relying on text-based prompts or stimuli. Researchers may consider altering their experimental design or restricting participant eligibility in such cases.

Many participants will likely have had little to no prior experience using Google Glass. Anecdotally, many of our participants commented on how "exciting" or "weird" Glass was. We recommend that researchers at least briefly introduce Glass to participants before beginning the experiment. An introduction to Glass minimizes participants' awkwardness with the device and reduces the chance that participants will interfere with key Glass capabilities during the experiment (e.g., by brushing the touchpad). Researchers may use our protocol—reported in the Materials and Procedure section—as a guide.

The framework is currently designed to protect data transfer between the server and connected Glass devices. Therefore, problems with wireless Internet connections can cause PsyGlass to terminate the data collection session or disconnect the Glass from the server entirely. All data prior to termination are still saved locally on the device. By prioritizing connectivity, PsyGlass is able to ensure that all commands are executed as intended, but this may be an issue for individuals who have unreliable or difficult wireless networks. This can currently be changed by reprogramming PsyGlass, and we hope to release an alternate version that is more forgiving in this area.

Researchers may consider applying down-sampling procedures, band-pass filters, or moving averages for their data analysis, depending on project needs and the standard practices of relevant target research area(s). The high-resolution movement data provide high statistical power for time series analyses, but this power may not always be needed. An example of data manipulation and filtering has been provided above in the Analyses section.

[8] Due to additional conditions outside of the scope of the present article.

[9] Measured from the nose of wearer to the nose of viewer in a well-lit room, with the viewer having normal, uncorrected vision.

3.5 General discussion

Wearable technology can provide researchers with opportunities to explore naturalistic behavior dynamics both in and out of the lab. PsyGlass capitalizes on Google Glass to give researchers a stimulus presentation and data collection tool in an easily customizable, open-source framework. We have provided an example application of PsyGlass to dyadic interaction research, but the paradigm is open to single- and multiparticipant studies. We welcome other researchers to join us in using or expanding PsyGlass on GitHub (www.github.com/a-paxton/PsyGlass). The openness of the Google Glass developer community stands as a resource for researchers interested in tapping into other dimensions of the Google Glass, from audio stimulus presentation to eye-camera recording.

3.5.1 Update regarding purchasing Google Glass

Google has recently shifted the Glass program to focus more on developers and enterprise needs through its "Glass at Work" program (https://developers.google.com/glass/distribute/glass-at-work). At the time of writing, those interested in purchasing Glass for research or educational needs may contact the Glass at Work program at glass-edu@google.com. Any changes or additional relevant information will be included on the readme file at the PsyGlass repository (http://github.com/a-paxton/PsyGlass).

3.5.2 Future directions for PsyGlass and wearable technology

Wearable solutions like PsyGlass and other tools (e.g., Olguín Olguín, Gloor, & Pentland, 2009) are helping researchers increase external validity and target the real-world behaviors that they are interested in exploring. Especially for complex behaviors like interaction, researchers must balance experimental controls with experimental designs targeting naturalistic behaviors. By providing wireless, portable, minimalistic behavior tracking, wearable technology can unobtrusively quantify behavioral metrics and give moment-to-moment control over stimulus presentation. These represent an addition to our tools for creating naturalistic, externally valid experiments that tap into the real-world behaviors we seek to capture. With PsyGlass, we hope to lower the barriers to entry for other researchers who are interested in capitalizing on these new opportunities.

In that vein, we intend to continue to expand PsyGlass as a methodological tool that can contribute to theoretical inquiry. Our basic goals include tapping additional Glass capabilities for data collection (e.g., gyroscope, eye-camera capture) and stimulus presentation (e.g., audio) to give researchers more experimental design and multimodal options. We have already created optional modules to implement lexical decision tasks on PsyGlass, available on GitHub. We hope to provide a suite of collection and presentation options that others can use to cobble together versions of PsyGlass that fit their needs. Our first goal for major expansion is to create a way for partners' Glass devices to be interactively updated by each another—for instance, by having the amplitude of movement of one Glass (measured by the accelerometer) update the visual stimuli of a second, connected Glass. In doing so, PsyGlass can subtly prompt interaction dynamics and alter interpersonal behaviors on the basis of prespecified events. By putting the code onto an open community for programmers, we hope to encourage others to join us in our expansion and refinement of the PsyGlass tool.

3.6 Author note

We thank UC Merced undergraduate research assistants Keith Willson, Krina Patel, and Kyle Carey for their assistance in data collection for the example PsyGlass application.

3.7 Appendix

3.7.1 Accessing PsyGlass Glassware (see Fig. 3.5)

Through the touchpad

Navigate to the Home card. Tap once to view a list of commands. Navigate to "Show Demo" and tap once. If you are not immediately taken to the PsyGlass immersion, navigate to "Sample Experiment" and tap once.

Through voice commands

Say "ok glass." A menu with a list of voice commands will pop up. Say "Show me a demo with." If you are not immediately taken to the PsyGlass immersion, say "Sample Experiment."

3.7.2 PsyGlass Glassware data collection flow (see Fig. 3.6)

Main activity

This is the first activity with which the user is presented. The user sees the title card and is prompted to tap the device for options. Tapping the device brings up an options menu with two items: "Start" and "Settings." Selecting the first option takes the user to the Game Activity, and selecting the second takes the user to the Settings Activity. Swiping down on the device will return the user to the Google Glass timeline.

Game activity

This is the activity in which the actual experiment and data collection take place. First, the device attempts to connect to the server, which must first be initiated from the experimenter console. Once connected, it will continuously poll the server for updates, and the server guides the device through the data collection session. During the session, the server dictates when the device should start collecting data, when it should change the display of the device, and when to stop collecting data. Data collection involves writing accelerometer sensor readings to a text file on a local device. Tapping the device brings up the options menu with the "Finish" item. Selecting this item forces the device to close its connection to the server, close the sensor, finish writing to the text file, and return the user to Main Activity.

Settings activity

This activity presents the Data card, which contains four fields with information. The first field shows the device ID, given to the device by the server at the start of the most recent experiment; device ID numbers begin at 0 and are assigned sequentially according to server connection order. The second and third fields show the date and time of when the session of the experiment was conducted. The fourth field shows the duration of the session of the experiment conducted. These fields on the card will be empty if no experiment has been conducted on the device. Tapping on the device with this card active will bring up an options menu with the “Upload Data” item, which allows the user to upload the data collected from the latest experiment. Selecting the item takes the user to the Upload Activity. Swiping down on the device will return the user to Main Activity.

Upload activity

This is the activity in which the application uploads data to the server. The application prepares the internal text file containing experimental data and streams the content to the server. Tapping on the device brings up the options menu with the “Cancel Upload” item. Selecting this item will close the text file, close the connection to the server, and return the user to Settings Activity.

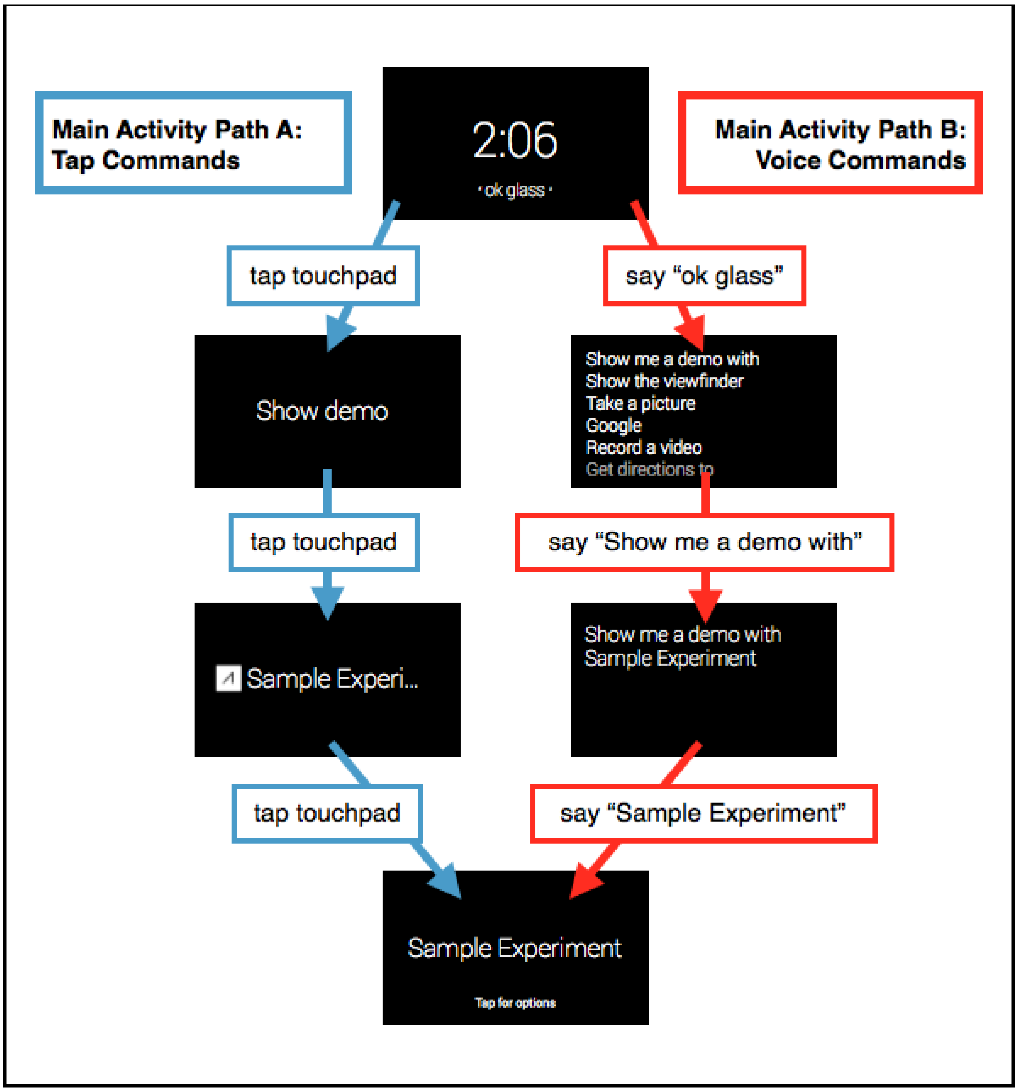

Figure 3.5: PsyGlass Glassware flow for navigating to the data collection study (“Main Activity”). The Main Activity can be accessed in two ways: navigating with the touchpad (Path A) or through voice commands (Path B).

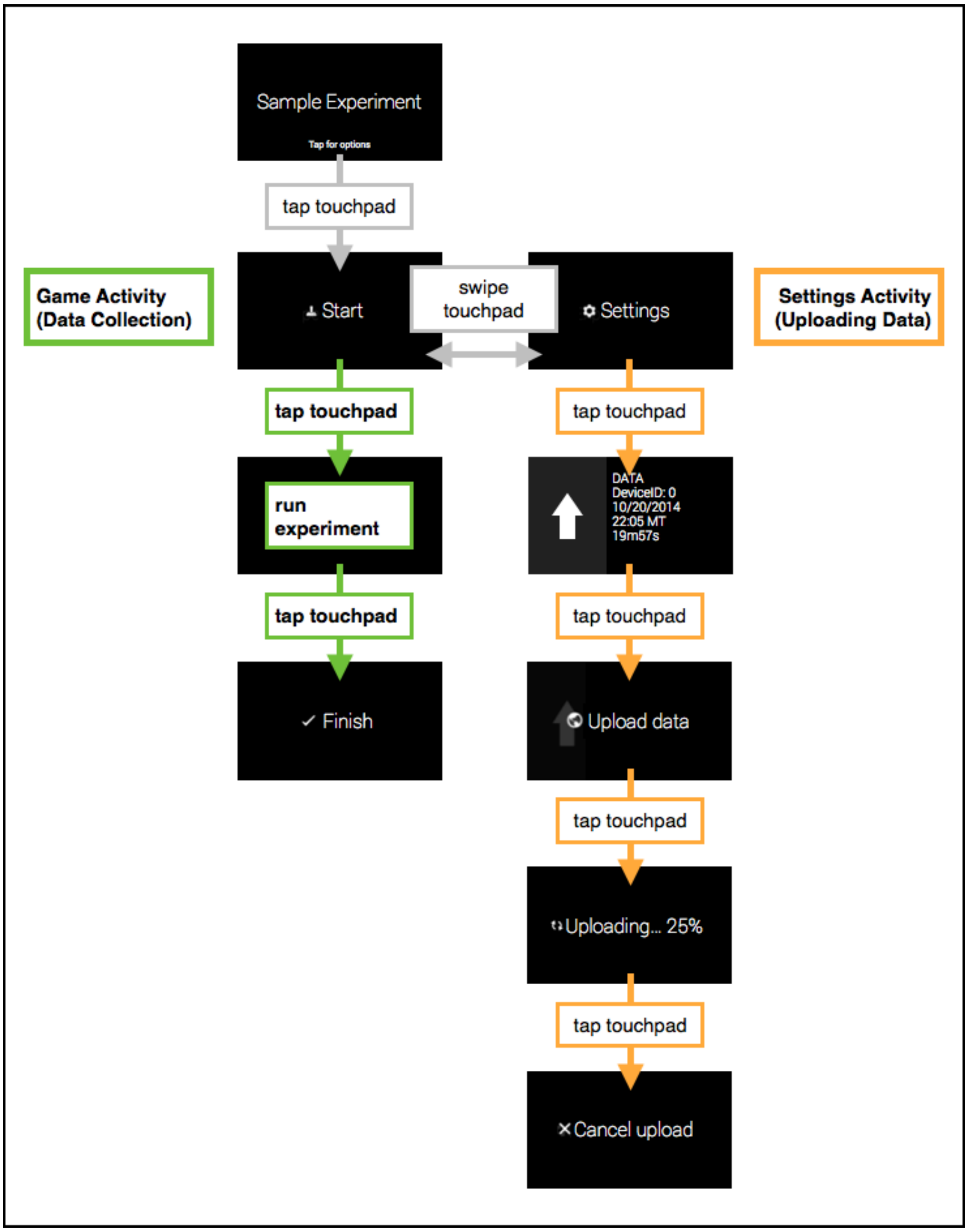

Figure 3.6: PsyGlass Glassware flow for initializing and terminating data collection (left; "Game Activity") and for uploading the session data to the server (right; "Settings Activity" leading to "Upload Activity").

Chapter 4

Context–dependent gaze coordination

4.1 Introduction

Decades of research on *interpersonal coordination* highlight the interconnectedness of the human social experience. From holding a conversation to solving a puzzle, we tend to become more similar over time in our speech (e.g., Niederhoffer & Pennebaker, 2002), affect (e.g., Randall et al., 2013), and movement (e.g., Chartrand & Bargh, 1999) through our shared experience. This similarity stretches across time scales, from correlations of the moment-to-moment fluctuations in a behavior (e.g., Hove & Risen, 2009) to overarching patterns in the statistical distributions of a behavior over time (e.g., Abney et al., 2014).

Although coordination appears to be nearly ubiquitous, growing work is beginning to establish limiting parameters. Communicative context—the type of interaction in which individuals are engaged—may be one crucial parameter that modulates interpersonal coordination. For example, compared to friendly interactions, conflict decreases coordination (e.g., Paxton & Dale, 2013a). The present study contributes to crucial unanswered questions about what might be driving these context-dependent changes in coordination.

4.1.1 Interpersonal Coordination, Rapport, and Comprehension

Despite vast evidence for the existence of coordination, its *purpose* is relatively less well understood. While the overarching nature of coordination is being currently being debated (cf. Riley et al., 2011; Abney et al., in press; Pickering & Garrod, 2004; Lakin et al., 2003), there are several properties of coordination that have received relatively widespread acceptance. In the present work, we examine two of these properties: the relation of coordination to social bonding and to comprehension.

First, coordination is closely tied to social bonding. Previous research consistently supports a bidirectional link between coordination and rapport. Both low-level (e.g., Hove & Risen, 2009) and higher-level (e.g., Chartrand & Bargh, 1999) motor coordination increases liking and rapport. Similarly, greater liking and rapport improves coordination (e.g., Lakin & Chartrand, 2003; Giles et al., 1991). Although the specific details and mechanisms of this relationship may be under some dispute, coordination is widely acknowledged as both rapport-building and rapport-reflective.

Second, coordination is linked to comprehension. A large portion of this research has focused on gaze coordination specifically, demonstrating how important the timing of joint visual attention is to understanding. Gaze coordination has been *causally* linked to comprehension (D. C. Richardson & Dale, 2005) and is sensitive to shared experiences and other forms of common ground (e.g., D. C. Richardson et al., 2012; D. C. Richardson, Dale, & Kirkham, 2007; D. C. Richardson et al., 2009). Other forms of coordination can also increase or facilitate comprehension, even while working together with gaze coordination (e.g., linguistic coordination; Dale et al., 2011). Interestingly, even *intrapersonal* coordination during speaking—the subtle, congruent timing of gesture and speech to complement one another—increases listener comprehension (Woodall & Burgoon, 1981). While this idea is pivotal to some theories of coordination (e.g., Garrod & Pickering, 2009; Pickering & Garrod, 2013), the ties to understanding are commonly accepted as an important property of coordination.

4.1.2 Conflict and Coordination

Traditionally, research on interpersonal coordination has tended to focus on task-based (e.g., Dale et al., 2011), affectively neutral (e.g., Condon & Sander, 1974), or affiliative (e.g., Chartrand & Bargh, 1999) interactions. This body of work has provided us with important insights into how we move (e.g., Chartrand & Bargh, 1999), feel (e.g., Randall et al., 2013), work (e.g., Dale et al., 2011), and talk (e.g., Niederhoffer & Pennebaker, 2002) together. Conflict, by contrast, has been relatively understudied within research on interpersonal coordination.

While conflict may be one of the most negative and unpleasant communicative contexts (Bell & Song, 2005), it follows us through our lives and social experiences (Birditt, Fingerman, & Almeida, 2005). Understanding its effects on the subtle but nearly omnipresent threads of coordination will help better characterize not only conflict specifically but coordination and interaction more broadly. To that end, recent efforts have begun to explore how conflict changes coordination (e.g., Paxton & Dale, 2013a; Abney et al., 2014).

Congruent with the idea that interaction is a highly adaptive complex system (e.g., Shockley et al., 2009; Abney et al., in press; Riley et al., 2011), conflict appears to drastically alter the structure of interpersonal coordination across multiple modalities. The subtle gross motor movement coordination usually seen in conversation disappears during conflict (Paxton & Dale, 2013a), and co-speech decreases significantly compared to friendly conversation (Paxton & Dale, 2013c). Even longer-scale distribution of speech turns becomes more dissimilar (Abney et al., 2014). Interestingly, conflict can increase *dysfunctional* coordination patterns: Stronger conflict is linked to increased coordination of negative affect (Main et al., under review).

Together, these findings suggest that conflict's inherent negativity (Bell & Song, 2005) and associated difficulties with perspective-taking (Frantz & Janoff-Bulman, 2000) may clash with the rapport-building effects of coordination (e.g., Hove & Risen, 2009). However, the reasons for these changes—especially the breakdown of coordination in movement and speech—are poorly understood. The present study explores potential causes by targeting a new domain for research in conflict and coordination: gaze.

4.1.3 The Present Study

The present study explores the context-sensitivity of gaze coordination. We take the view that conversation is a complex adaptive system (Paxton et al., in press). As such, patterns of gaze coordination should be sensitive to various individual and interpersonal environmental constraints (e.g., goals; Shockley et al., 2009).

Here, we examine conversational context as one possible environmental constraint. The present study explores whether congruency of opinion—either *agreeing* or *disagreeing* with a given opinion—will modulate gaze coupling between speakers and listeners. However, as the first explicit exploration of conflict's effects on gaze coupling,[1] we approached the study with competing hypotheses about two possible outcomes. In both cases, we anticipate that coupling between speakers and listeners will be slightly time-lagged; listeners should demonstrate the same gaze dynamics as the speaker but with a slight delay (D. C. Richardson & Dale, 2005).

Gaze coordination (or coupling) between speakers and listeners has been causally linked to increased comprehension (D. C. Richardson & Dale, 2005). A proposed mechanism for this coordination is tied to the effects of language on joint attention (D. C. Richardson et al., 2007): As speakers allude to objects within the environment, listeners attend to the relevant object while processing incoming speech. Therefore, we may see that gaze coordination is not affected by the communicative contexts under consideration here. One hypothesis (H_1) is that gaze coordination *remains unchanged*, regardless of opinion congruency.

H_1**:** *Gaze coupling between listeners and speakers with congruent opinions should not significantly differ from gaze coupling between listeners and speakers with incongruent opinions.*

At the same time, conflict is associated with a sharp decrease in coordination other communication channels (e.g., Paxton & Dale, 2013c, 2013a; Abney et al., 2014). We may find that conflict or disagreement has a similar effect on gaze; the driving mechanism behind gaze coupling (e.g., joint attention) may also be sensitive to high-level cognitive constraints. Accordingly, the second hypothesis (H_2) is that gaze coordination *decreases* for incongruent opinions (i.e., disagreement), as compared with congruent opinions (i.e., agreement).

H_2**:** *Gaze coupling between listeners and speakers with congruent opinions should be significantly higher than gaze coupling between listeners and speakers with incongruent opinions.*

A major goal of the current study is to help shed light on the mechanisms leading to the decrease in coordination during conflict. If our results support H_2, it may suggest that conflict may be characterized by a fundamental lack of understanding. Essentially, under this perspective, the lack of coordination we see in movement and speech may reflect a lack of common ground, perspective-taking, or other cognitive alignment. The failure to be "on the same wavelength" may resonate through the interpersonal system, disrupting coordination.

However, if our results support H_1, it may suggest that the breakdown in coordination that we see in other behaviors during conflict is not due simply to a lack of comprehension. Again, given the causal link between comprehension and coordination (D. C. Richardson & Dale, 2005), we may find that interlocutors are perfectly capable of comprehending their partner. Viewing conversation as a complex adaptive system, not all perturbations will affect each subsystem similarly; support for H_1 would suggest that the mechanisms underlying gaze coupling are resilient in the face of conflict.

4.2 Method

4.2.1 Participants

Participants were 50 undergraduate students from the University of California, Merced (mean age = 20.12 years; females = 30). All received course credit as com-

[1] D. C. Richardson et al. (2009) examined gaze coupling during discussions of controversial topics, but differences of opinion between interlocutors were not analyzed.

Table 4.1: Summary of total speaker data. Breakdown of percentage of speakers (with n in parentheses) in each opinion of each topic, along with whether speakers showed a majority of one opinion on a topic ("dominant-view") or whether speakers' opinions were relatively equally divided between the two ("mixed-view"). Asterisk indicates majority opinion in "dominant" topics.

Topic Class	**Topic**	**Opinion**	**Speakers**
dominant-view	abortion	neither	11.1% ($n = 3$)
		pro-choice *	74.1% ($n = 20$)
		pro-life	14.8% ($n = 4$)
	higher taxes for rich Americans	against	22.2% ($n = 6$)
		for *	66.7% ($n = 18$)
		neither	11.1% ($n = 3$)
	legalizing marijuana	against	18.5% ($n = 5$)
		for *	77.8% ($n = 21$)
		neither	3.7% ($n = 1$)
	marriage equality	against	3.8% ($n = 1$)
		for *	92.3% ($n = 24$)
		neither	3.8% ($n = 1$)
mixed-view	death penalty	against	50% ($n = 13$)
		for	42.3% ($n = 11$)
		neither	7.7% ($n = 2$)
	"junk food" tax	against	56% ($n = 14$)
		for	44% ($n = 11$)
	lowering U.S. drinking age	against	50% ($n = 13$)
		for	50% ($n = 13$)

pensation. All participants reported conversational fluency in English and normal or corrected-to-normal hearing and vision.

Each participant was recruited as a member of one of two groups: speakers (included $n = 4$; females $= 3$) and listeners ($n = 46$; females $= 27$). An additional 18 participants were recruited as listeners (with similar demographic characteristics) but were not included because of technical problems during data collection. Technical problems during data collection also resulted in the loss of some segments for some of the included 46 listeners (mean trials per included listener $= 8.74$; mean included listeners per segment $= 40.2$).

4.2.2 Materials and Procedure

After the informed consent process, all experimental procedures were performed through SMI's Experimenter Center software (version 3.5; SensoMotoric Instruments, 2015). Participant gaze was tracked throughout the experiment with SMI's RED-m remote eye tracker. The eye tracker was calibrated once at the beginning of the experiment and was re-calibrated prior to each topic.

All participants first completed a brief demographics survey and a sociopolitical questionnaire. Similar to some of our previous work (Paxton & Dale, 2013a), the questionnaire asked participants to write their opinions about seven (7) topics with neutrally worded prompts, presented in random order: abortion, legalization of marijuana, the death penalty, marriage equality,[2] "junk food" tax, lowering the U.S. drinking age to 18 years old, and whether rich Americans should be taxed at a higher rate. After

[2]Described to participants as "gay and lesbian marriage."

writing his or her opinion in an open-response text box, each participant then indicated his or her opinion strength for that topic on a 1 (*feel very weakly*) to 4 (*feel very strongly*) scale.

These seven topics formed the foundation of the current experimental materials. During each of the target trials (described below), participants were shown a collage about each topic. Each collage comprised six (6) images (all of relatively similar size) balanced for valence, size, and visual information. Participants in the **speaker** group viewed each collage while producing a persuasive monologue about the topic. Participants in the **listener** group viewed each collage while listening to one of the related persuasive monologues produced by a participant in other group. We describe the unique features of data collection for each group below.

Speakers

After completing the demographics survey and opinion questionnaire, speakers were given written instructions to explain their opinions about several topics out loud. Speakers were instructed to discuss only the given topic and very related topics during each monologue, to take as much time as needed to fully explain their opinion, and to try to be as persuasive as possible. These instructions were presented before beginning the monologue production phase and again on each slide presenting a new topic. All topics were presented in random order.

Twenty-seven (27) students participated in this phase for course credit, although equipment error resulted in the loss of some monologue topics for some speakers (see Table 4.1). From these data, we selected only the most passionate, persuasive monologue for each side of each topic as stimuli for the listener phase. Two trained research assistants blind to study hypotheses rated each monologue on two, five-point scales (i.e., passion and persuasiveness). The 5-point scales were then collapsed into ratings of low (1-2), medium (3), and high (4-5). Linear-weighted Cohen's kappa—a measure of interrater reliability—between the two raters reached .72 for passion and .75 for persuasiveness. Of the 27 total speakers, 20 gave permission to use their monologues as stimuli in the next phase. We narrowed these released monologues to include only those that lasted at least 80 seconds and were rated as high in both passion and persuasiveness by both raters. (We refer to these as "candidate monologues" below).

Unexpectedly, we found that 4 of the 7 topics failed to solicit monologues rated as high in passion and persuasiveness by both raters: abortion, legalization of marijuana, marriage equality, and taxation of rich Americans. In these topics, at least two-thirds (66.7%) of speakers endorsed a single side (see Table 4.1). The remaining 3 topics were represented by roughly equal numbers of monologues on each side of the topic across all speakers and included candidate monologues on both sides of the issue. We will refer to the former as *dominant-view* topics and to the latter as *mixed-view* topics, due to the distribution of opinions on the topic *in our sample*. We discuss this further in the Analysis section.

From the candidate monologues, we identified 10 monologues from 4 speakers (as reported in the Participants section). Some topics and/or sides of topics were represented by only one candidate monologue; in these cases, we used this monologue. If multiple candidate monologues existed for one side of any given topic, we chose the stimuli to maximize the number of unique speakers in our stimuli and to control for monologue length. For the dominant-view topics with multiple candidate monologues, we selected monologues that were close in length to the mean duration of the chosen stimuli for the other 3 topics.

Listeners

After completing the demographics survey and opinion questionnaire, listeners were told that they would be listening to a number of other people's opinions about various topics and that they would be asked questions immediately following each opinion. All listeners were then presented each of the 10 monologues—presented in random order—by over-ear headphone. Immediately following each monologue, listeners were asked five (5) randomized Likert-style questions about the monologue, including a question of how much the listener agreed with the speaker overall (from *strongly disagree [1]* to *strongly agree [4]*).

4.2.3 Analyses

Planned Analyses

We quantified the coordination between speakers' and listeners' gaze patterns during each monologue using *cross-recurrence quantification analysis*, a nonlinear data analysis technique that quantifies similarities in states between signals. As with D. C. Richardson and Dale (2005), the present study is interested in exploring the similarities between the gaze time series of speakers producing a monologue and listeners hearing the same monologue. Essentially, CRQA allows us to explore whether participants' gaze patterns explored similar regions of the screen over time. CRQA views the speaker-listener pair as a system and characterizes that system with a variety of different parameters. For more on CRQA and recurrence quantification analysis, Marwan (2008) and Coco and Dale (2014) provide excellent reviews.

We performed CRQA between the speaker and each listener for each monologue (cf. D. C. Richardson & Dale, 2005). We designated areas of interest (AOIs) for each image in each collage. Speaker and listener gaze patterns relative to these AOIs were downsampled from 120 Hz to 100 Hz. We then performed CRQA over each listener-speaker time series pair using the `crqa` package (Coco & Dale, 2014) in R (R Development Core Team, 2008). The resulting *recurrence rate* quantifies to what degree the speaker and listener gaze patterns were coupled during the monologue.

Our planned analyses primarily explore differences in coordination patterns by opinion congruence (i.e., listener's agreement or disagreement with the speaker). Using CRQA as our measure of gaze coupling, we will examine how and whether the relative time course (i.e., lag) of gaze dynamics is affected by the higher-level cognitive conditions of opinion congruence.

Exploratory Analyses

As mentioned in the Materials and Procedure section, we found an unexpected pattern in the speaker monologues: Some topics clearly had a dominant opinion, while views of other topics were split across roughly equal numbers of speakers (see Table 4.1). Because we did not expect to find these differences in the distributions of speaker opinions, we did not begin the experiment with hypotheses about differences between dominant-view and mixed-view topics. However, we believed that exploring these differences could shed light on whether the broader social environment—either itself or through an interaction with personal opinion—alters patterns of gaze coordination. This could provide important insights into how larger-scale social context might shape individual dynamics.

Importantly, we do not claim that (1) the dominant-view topics nor (2) the majority opinion within the dominant-view topics identified in our sample are themselves universally dominant. We recognize that there are a wide variety of opinions on these topics and that distributions over these opinions likely differ by region and community. Using the opinions of the community from which our speaker sample was taken, the present analysis may shed light on how *majority opinions* broadly—rather than the *specific opinions* included here—might shape gaze dynamics.

4.2.4 Data Preparation

Given participant freedom method afforded by the desktop-mounted eye tracker, our data—especially the listener data—were characterized by significant portions of missing data (i.e., eye tracking samples in which participants' gaze were recorded as looking at something other than the computer screen). On average, listening trials were missing gaze data for approximately 33% of possible samples (again, taken at 100Hz). We believe this is due to two parameters of the task. First, the unobtrusive eye tracker allows listeners to engage in naturalistic gaze and movement patterns rather than restricting them to look only at the screen. All participants were told that they would be eye-tracked during the experiment, but we included no explicit instructions to look only at the screen, since we did not want to change their natural gaze patterns.

Second, the visual stimuli were abstractly related to the audio clips, but they were not as concretely related as previous similar work (cf. pictures of characters in the speaker's narrative; D. C. Richardson & Dale, 2005). As a result, these images may have been somewhat less compelling to the listener. This may have exacerbated the first concern, as participants may have been less invested in looking at the accompanying images.

We dealt with these missing data by matching speakers and listeners for each time point for each pair. For each pair, we then excluded any time points at which either speaker or listener had missing data. Unfortunately, this problem led us to exclude all data for the "against" side of the "lowering U.S. drinking age" segment, but the mean number of listeners per included segment was identical ($M = 40.2$).

These missing samples also lead to interesting concerns with interpretations of the CRQA analyses. CRQA is typically used to explore the timing of events relative to one another, using the sampling rate as a means of anchoring the relative time scale (cf. D. C. Richardson & Dale, 2005; Main et al., under review). In order to interpret CRQA analyses in this way, the time series over which CRQA was calculated must have largely regular, reliable sampling. The missing data in our time series therefore preclude us from making any strong claims about the interpretation of such timing. Instead of interpreting the timing of the lag, we will only be able to address the relative dynamics over time—whether broad, time-free patterns in coordination change as the relative time between listener and speaker gaze events increases or decreases.

4.3 Results

To quantify coordination, we relied on recurrence (*%rec*) within a window of ±300 samples, consistent with previous research (D. C. Richardson & Dale, 2005; Paxton & Dale, 2013a; Abney et al., in press). Listeners' self-reported Likert-style ratings were dummy-coded into a dichotomous variable of broad disagreement (0; originally, 1-2) and broad agreement (1; originally, 3-4). Agreement ratings were skewed positively: Listeners self-reported broad agreement with the speaker in 67.7% of all 362 ratings.

4.3.1 General Patterns

Our first analyses of general recurrence patterns largely focused on two metrics of CRQA: maximum recurrence and maximum lag. *Maximum recurrence* simply takes the maximum recurrence value (%rec) of each speaker-listener gaze time series within the ±300-sample window. *Maximum lag* is the relative lag at which maximum recurrence occurred for each speaker-listener pair.

A one-sample t-test showed that the maximum lag for all speaker-listener pairs was significantly different from 0, $t(361) = 31.17$, $p < .0001$. Separate t-tests confirm that these differences hold for both agreement ($t(244) = 26.19$, $p < .0001$) and disagreement ($t(116) = 16.99$, $p < .0001$). This supports previous research that finds a reliable delay between speakers' and listeners' coupled gaze patterns (D. C. Richardson & Dale, 2005).

Similar results hold for tests of maximum recurrence. A one-sample t-test showed that maximum recurrence for all speaker-listener pairs significantly differ from 0, $t(322) = 30.89$, $p < .0001$. Again, t-tests confirm these patterns hold during listener agreement ($t(217) = 27.73$, $p < .0001$) and disagreement ($t(104) = 15.68$, $p < .0001$).

A one-sample t-test showed that the maximum lag for all speaker-listener pairs was significantly different from 0, $t(361) = 37.63$, $p < .0001$. Separate t-tests confirm that these differences hold for both agreement ($t(244) = 34.63$, $p < .0001$) and disagreement ($t(116) = 18.75$, $p < .0001$). This supports previous research that finds a reliable delay between speakers' and listeners' coupled gaze patterns (D. C. Richardson & Dale, 2005).

Despite visual trends (see Figure 4.1), we find no reliable differences in maximum lag and maximum recurrence by opinion congruence. Mean maximum lag was 317.59 samples for listener agreement and 286.92 samples for listener disagreement. Mean maximum recurrence was 0.24 for listener agreement and 0.27 for listener disagreement. Two separate linear mixed-effects models[3] revealed no significant effect of congruence played in predicting maximum recurrence (B = -0.02, $p = .44$) but found a trend towards a significantly higher maximum lag (i.e., longer delay) in agreement (B = 34.99, $p = .10$).

4.3.2 Planned Analyses

After the brief exploration of basic patterns and differences, we moved on to our planned analyses. Data were analyzed with a series of linear mixed-effects models using audio clip and listener as non-nested random intercepts with maximal allowable random slopes. All variables—including interaction terms—were centered and standardized prior to being entered into these models. Standardizing the data allows the resulting β values to be interpreted as effect sizes (cf. Keith, 2005). Linear mixed-effects models were built with the `lme4` package (Bates, Mächler, Bolker, & Walker, 2015) in R (R Development Core Team, 2008).

The first model predicted recurrence (%rec) with opinion congruence and lag. Neither the main effect of lag ($\beta = .05$, $p = .19$) nor the interaction of lag and opinion congruence ($\beta = -.03$, $p = .43$) reached statistical significance. The main effect of opinion congruence ($\beta = .003$, $p = .07$) trended toward but did not reach significance.

Given the nonlinear shape of the data (see Figure 4.1), we used growth curve analyses to model the unfolding of the data over lag (Mirman, Dixon, & Magnuson, 2008; Mirman, 2014). While growth curve analyses emerged to model patterns over time (e.g., Paxton, Roche, & Tanenhaus, 2015), it can also be used to model patterns in *relative* time or lag (e.g., Main et al., under review). In the next model, we include linear (first-order orthogonal polynomial) and quadratic (second-order orthogonal polynomial) lag terms. Including both first- and second-order orthogonal polynomial terms decouples linear and quadratic lag from one another, allowing each to be interpreted independently in the model results (Mirman et al., 2008). As mentioned earlier, we cannot interpret the time course of these effects precisely due to the missing data, but the time-free relative patterns reflected in the analyses should provide insight into the gaze dynamics.

[3] With maximal random intercepts for listener and audio clip.

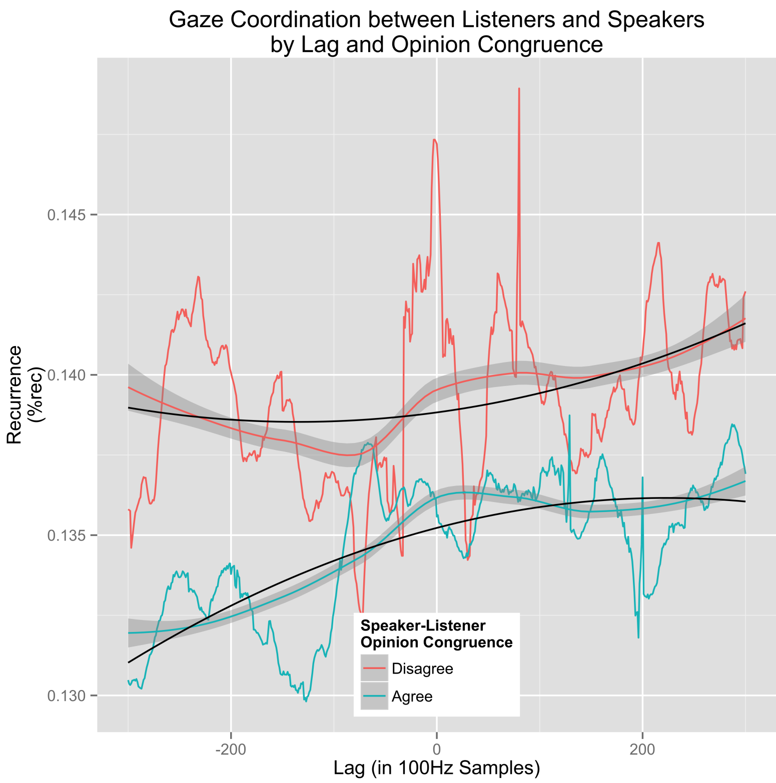

Figure 4.1: Gaze coordination by lag and opinion congruence between speakers and listeners. Shaded bars indicate standard error. Second-order polynomials are fitted (in black) over each group. Negative lag indicates a listener-leading trend in gaze patterns; positive lag indicates a speaker-leading trend. Plot generated in R (R Development Core Team, 2008) with `ggplot2` (Wickham, 2009).

Our second model predicted %rec with opinion congruence, linear lag, quadratic lag, and all possible two-way interactions. (We chose not to include the three-way interaction to simplify interpretability of all possible effects.) Main effects for linear lag (β = .02, p = .54), quadratic lag (β = -.01, p = .82), and opinion congruence (β = -.002, p = .98) all failed to reach statistical significance, as did the interaction term between linear and quadratic lag significance (β = -.002, p = .50). However, the two-way interaction terms for opinion congruence with linear lag (β = .01, p <.0001) and quadratic lag (β = -.01, p <.005) both reached significance with relatively small but reliable effects on gaze coupling.

Taken together, results from our planned analyses partially support both H_1 and H_2. As demonstrated in Figure 4.1, the significant interaction term between opinion congruence and quadratic lag is indicative of a tighter temporal coupling of gaze in the agreement condition. The interaction between linear lag and opinion congruency further supports the existence of a stronger effect of temporal coupling among those who agree: While there may be more pervasive coupling for listeners who disagree, there appears to be a sharper jump in coupling around synchrony (lag 0) with the speaker's gaze. In other words, although disagreement does not significantly decrease the overall amount of gaze coordination (supporting H_1), we do find that agreement the moment-to-moment unfolding of the gaze dynamics by leading to a tighter temporal coupling at a faster rate (supporting H_2).

4.3.3 Exploratory Analyses

Our next set of analyses explored how topic class—whether opinions on the topic are dominated by a single view or are relatively equally distributed across multiple perspectives—influences gaze coupling. As with our models in the Planned Analyses section, we analyzed the data with a series of mixed-effects models, with all terms having been centered and standardized prior to model creation. All models were created with the maximal random effects structure permitted to achieve convergence.

The first exploratory model predicted %rec with lag, opinion congruence, and topic class, along with all two-way interactions. (Again, the three-way interaction was not included in order to simplify interpretations of results.) Lag (β = .02, p = .58), topic class (β = .11, p = .34), and opinion congruence (β = .01, p = .85) failed to achieve significance as main terms in the model. The model also found no significant effects of the interaction terms between topic class and lag (β = .006, p = .80) and topic class and opinion congruence (β = -.006, p = .91). The interaction of lag and opinion congruence again contributed a small but reliable effect to the model (β = .01, p <.0001).

The second exploratory model included linear and quadratic lag terms (as described previously), opinion congruence, topic class, and all possible two-way interactions. In this model, we again find significant effects only for the interaction between linear lag and opinion congruence (β = .01, p <.0001) and quadratic lag and opinion congruence (β = -.006, p <.0001). All other effects failed to reach significance in the model (all ps >.40).

The results from these two models suggest that the general social consensus around a given topic—that is, whether the topic is currently contentious within a specific social environment—does not account for our observed effects of gaze coordination in the current dataset. Results suggest that personal agreement or disagreement plays a more important role in characterizing the gaze dynamics than does the wider social consensus at the time.

4.4 Discussion

During conversation, the ability to coordinate attention is crucial to mutual understanding. However, different communicative contexts bring with them unique interpersonal (and intrapersonal) pressures. While the major goal in listening to a story may simply lie in following the narrative arc, responses to charged sociopolitical opinions—especially *opposing* opinions—may not be so straightforward. The current research is the first to explore this idea by quantifying gaze coordination between speakers and listeners in unscripted persuasive monologues.

While previous research supports the importance of gaze coordination during storytelling narratives (D. C. Richardson & Dale, 2005), the present work addresses how personal opinion affects how gaze coordination. We began with two competing hypotheses: that gaze coupling would be unaffected in the face of disagreement (H_1) or that gaze coupling would be significantly lower in the face of disagreement (H_2). The results of several models partially supported both competing hypotheses. While we found no significant effect of opinion congruence on the overall amount of gaze coupling, we did find that a listener's gaze tended to be more tightly coupled in time to the speaker's when he or she agreed with the speaker's opinion.

4.4.1 Coordination in Conflict

This pattern of results supports the idea of coordination as being an emergent, context-sensitive property of interaction (Paxton et al., in press). Previous work has found that conflict decreases coordination of body movement (Paxton & Dale, 2013a) and speech (Abney et al., 2014), but the present analyses suggest that conflict (or disagreement) may not exert a universal coordination-breaking effect on behaviors. Instead, we find that rates of gaze coupling are no different in agreement than in disagreement—with a trend toward significantly *higher* recurrence in disagreement. Therefore, the present work suggests that the gaze system is robust to conversational context as a perturbation.

The subtle differences between gaze patterns across opinion congruence suggest that we cannot attribute the decrease in coordination observed in other behavioral channels (e.g., Paxton & Dale, 2013a; Abney et al., 2014) to simple misunderstanding or failure to coordinate attention. Given the causal link between gaze coupling and comprehension (D. C. Richardson & Dale, 2005), if the effects of argument were reducible to a failure in comprehension, we would expect to find some evidence of this in the gaze coupling data. However, the current data cannot support simple communication breakdown as the explanation for conflict's negative effects on other types of behavioral coordination.

While this single study cannot completely rule out lack of understanding as a contributor to breakdown in coordination observed during conflict, its lack of effect in the present study may help suggest alternative mechanisms. For example, previous studies on conflict and coordination have relied on studies of face-to-face interaction (e.g., Paxton & Dale, 2013a; Abney et al., 2014), standing in contrast to the present study's non-interactive contexts. Social dynamics (e.g., saving face, *pro forma* social behavior)—which may be functionally nonexistent when sitting and listening to a recording by oneself—may therefore be a good candidate for the decrease in coordination observed during conflict.

4.4.2 Understanding Gaze Coordination

In addition to deepening our understanding of coordination's context sensitivity, the present work also contributes to research of gaze coordination more broadly.

There are several salient differences between the present study and the previous work on which we are building (D. C. Richardson & Dale, 2005). First—and most importantly—the present study used naturalistic, unplanned persuasive monologues with tangentially related visual stimuli, rather than images of characters directly related to the speaker's narrative. The different nature of the visual stimuli in the present study may contribute to the relatively lower amount of gaze coupling found in the present data (cf. maximum recurrence of .14-.16 in D. C. Richardson & Dale, 2005).

Second, the free-form nature of the current monologues may have provided a less linear structure than a narrative arc based on an episode of a mutually familiar television sitcom. The images presented to participants here were abstractly related to the topic, but in our careful listening to these audio clips, we found very few (if any) explicit references to any of the images by speakers. Furthermore, the images were not deeply related to one another beyond the broad topic at hand. This may have led to a less predictable stimulus for listeners, further decreasing the amount of gaze coordination.

Despite these differences, however, we still find gaze coupling between speakers and listeners in the present study. This suggests that gaze coordination is robust (but still sensitive) to the informativeness and richness of the visual environment. Even in the face of the relatively *less* explicitly informative or salient visual information, listeners and speakers spontaneously couple their gaze, supporting previous claims of the importance of gaze coordination to communication (D. C. Richardson & Dale, 2005).

4.4.3 Limitations and Future Directions

The current work has several limitations. First, listeners were overall more likely to report broad agreement with a speaker's opinion than broad disagreement. By asking listeners to report whether they agreed or disagreed with each monologue, we allowed their opinions to be somewhat "fuzzy": Listeners could report agreeing with both sides of an issue. This allows for a much more flexible and realistic understanding of opinion formation and beliefs, but the skewed agreement distribution should nevertheless be controlled or addressed in future studies. Future work may attempt to get more equal distributions of agreement with opinions, perhaps using more opinionated populations (e.g., those with strong political affiliations) or more polarizing topics.

It may also be useful to question listeners more thoroughly on the nature of this agreement or disagreement, perhaps by asking them why exactly they agree or disagree. Although we solicited listeners' written opinions about these topics before they began the listening phase, we chose to rely on listeners' own self-reports of agreement or disagreement. A close examination of possible differences between initial stances and later agreement ratings could provide interesting insights into patterns of opinion flexibility and cognitive processes.

The second major limitation lies in the missing gaze time series data. The desk-mounted eye tracker we used allows us to capture more naturalistic gaze behavior, but that freedom can lead to more limited data. Future data analysis may consider video-recording listeners to account for their behavior. For example, there may be interesting interactions between opinion congruence and a listener's willingness to engage with the on-screen stimuli. Recording participants' behavior would provide important additional data to dive more deeply into these questions.

Finally, future work may also include presenting highly persuasive monologues for non-dominant perspectives in dominant-view topics as well. While we provided some preliminary analyses of topic class (i.e., dominant- vs. mixed-view topics), none of our speakers produced sufficiently persuasive non-dominant perspectives for dominant-view topics. Comparing gaze dynamics during strong opinions on each side of both topic classes is needed to rule out possible alternative explanations for our exploratory analysis models.

4.4.4 Conclusion

Gaze coupling between speakers and listeners plays a vital role in facilitating communication by increasing understanding. Here, we present evidence that gaze coupling is robust to personal opinion. Using spontaneously generated persuasive opinions about controversial topics, we found that disagreeing with someone else's opinion did not lead to lower overall amounts of gaze coupling. Our findings stand in contrast to previous findings that coordination of other behaviors—like speech and movement—decrease during disagreement and conflict. We see our results as further support for viewing coordination as an emergent, context-sensitive property of interaction.

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Chapter 5

Discussion

5.1 Introduction

Research on interpersonal coordination provides valuable insights into an essential part of human behavior and the human social experience. However, as a relatively new research area, coordination still faces numerous important issues. Many of these issues are tightly linked, and effective solutions to the problems will address multiple issues from interdisciplinary perspectives.

This dissertation has addressed three important current problems within the interpersonal research area from such a perspective. Chapter 2 used computational modeling and large-scale data analysis tools for a data-driven analysis of nearly a dozen related terms within the field. Chapter 3 presented an open-source method for extending experimental control and objective quantification of behavior in naturalistic paradigms. Finally, Chapter 4 applied eye tracking—a classic cognitive science research method—to support the view of coordination as an emergent property of conversation. Below, I summarize the important findings and contributions from each of these chapters.

5.2 Data–Driven Explorations of Terminology

One of the single biggest problems facing coordination research is—arguably—the confusion over the terms used to describe the phenomenon and how these terms relate to one another. We can find research under over a dozen different terms, from *alignment* to *synergy*. To make matters worse, nearly all of these terms are used in wildly different contexts with a host of subtle meanings, with no clear or agreed-upon understanding of their relations to one another. This problem has a variety of serious consequences for the field, like creating isolated pockets of findings for different terms with very little cross-pollination among them.

At least two qualitative attempts have been made to create taxonomies related to this research area. Both Delaherche et al. (2012) and Butler (2011) tied their work closely to the methodology used to study the phenomenon, but each did so within separate realms. Butler's analysis largely focused on affective similarity and influence; Delaherche et al. took a wider view of the field. Both of these were excellent, useful works, but both were subjective interpretations of the terminological landscape.

Chapter 2 contributes a quantitative perspective on this issue. The paper—which will be submitted for publication with coauthor Rick Dale—capitalizes on large-scale text analysis tools for an objective look at the uses of these terms across the research area. We collected and analyzed a novel corpus of over 2,500 abstracts on interpersonal coordination and 10 other common and/or theory-related terms with two broad goals. We sought to identify (1) the dimensions that best characterized differences within this field and (2) a few possible terms that could be possibly be used as theory-free catch-all terms to describe the phenomenon.

To achieve these goals, we analyzed the corpus with three complementary analyses: latent semantic analysis (Landauer et al., 1998), latent Dirichlet allocation (Griffiths & Steyvers, 2004), and deep learning methods (Mikolov, Sutskever, et al., 2013). In line with our first goal for the paper, we explored the semantic space to identify natural groups among the data broadly. Our results pointed to research topic—whether researchers are studying similarity in language, movement, or neural activity—as generating the most descriptive clusters within the data. We found that the meanings of these terms, then, were not as well-defined as some claim.

In keeping with our second goal, after comparing the existing usage patterns for each term across the corpus, we identified *coordination* as the best candidate for a general term, with *synchrony* as a potential second. We chose the term based on its relatively diffuse (i.e., not specialized) meaning across the research area, along with its hub-like connections with numerous other terms. Hopefully, proposing an "umbrella" term based on properties of current use will facilitate its adoption, even if only as a relatively blunt tool while the field grapples with a more refined solution to the problem.

Beyond its immediate relevance to the field of interpersonal coordination, Chapter 2 also serves as a proof of concept for the usefulness of scientometric analyses for conscious theory-building. Previous work has already established the value of scientometrics in characterizing science writ large (e.g., Griffiths & Steyvers, 2004) or within a broad domain of science (e.g., Bergmann et al., accepted) Rather than supplanting careful thought and reasoning, this chapter provides an example of the usefulness of corpus analysis tools in better understanding a single subfield of research through data-driven insights.

5.3 Developing and Deploying Methods

A constellation of important concerns surrounding the current methodology of the research area can broadly be grouped into two clusters. First, we must balance concerns of external validity with the need for experimental control. Many researchers have developed clever and resourceful solutions to this problem (e.g., Miles et al., 2010), but we must continue to find new ways of facilitating careful experimental control in naturalistic settings.

Second, we need to find unobtrusive, scalable, and resource-effective methods to objectively quantify interpersonal coordination. While the field is moving away from labor- and time-intensive hand-coding analyses (cf. Condon & Sander, 1974), possible replacements have been adopted relatively slowly. Ideally, these new alternatives should be relatively affordable, easily implemented, and widely available to provide a low barrier to entry for interested researchers of all experience levels, skill sets, and funding capabilities.

Especially given the importance of timing to the phenomenon, we must take advantage of the growing availability of relatively cheap computational power to achieve these goals. Doing so will allow the field to move toward automatic objective analysis of movement, speech, affect, and other behavioral channels while minimizing investments of time and funds. One prime candidate for such methods, then, lies in wearable technology.

Toward that end, my collaborators and I developed PsyGlass (Paxton, Rodriguez, & Dale, 2015), an open-source application for Google Glass to facilitate naturalistic experimental designs. This project pairs a commercially available product with collaborative-friendly code to provide researchers with strong experimental control and high-resolution data collection. PsyGlass can easily be tailored to a variety of situations, but it was specifically created to facilitate our study of interpersonal coordination. Chapter 3 of this dissertation presented PsyGlass, a brief history of wearable technology in cognitive science-related research, and a brief example of how PsyGlass can be deployed in a study of interpersonal coordination.

5.4 Building Theory through Experiments

Within research on interpersonal coordination, a relatively new but rapidly growing perspective views coordination as an emergent property of conversation, proposed to be a complex dynamical system (e.g., Riley et al., 2011; Dale et al., 2014; Fusaroli & Tylén, 2012). One idea associated with this perspective, then, is that coordination should be context-sensitive, adapting and responding to the pressures exerted by the environment. Previous experimental work has found support for this idea by noting context-induced changes in the function and appearance of coordination in body movement (Paxton & Dale, 2013a), speech (Abney et al., 2014), language (Fusaroli et al., 2012), and more. In my final chapter, I present experimental evidence—to be submitted with coauthors Rick Dale and Daniel C. Richardson—that explores the context-sensitivity of gaze coordination.

Previous work has shown that speakers' and listeners' gaze patterns become coordinated (or coupled)—albeit with a brief delay—during interaction. For example, D. C. Richardson and Dale (2005) found that participants who are listening to a recorded narrative about a television sitcom episode will exhibit the same gaze patterns as the speaker who produced the monologue (with an approximately 2-second delay). Furthermore, gaze is an incredibly interesting test case for the context-sensitivity of coordination given its causal link between gaze coordination and understanding (D. C. Richardson & Dale, 2005).

Chapter 4 extends these findings to explore gaze coordination during disagreement. Combining gaze and conflict allows us to simultaneously examine the context-sensitivity of gaze coordination and investigate a possible mechanism for the decrease in behavioral coordination often seen in conflict (e.g., Paxton & Dale, 2013a; Abney et al., 2014).

To answer these questions, we recorded persuasive monologues on 7 contentious sociopolitical topics, along with the gaze patterns of the speakers. We later presented these recorded monologues to other participants while tracking their gaze and then asked the listeners to rate their agreement with each speaker. Analyzing these data with CRQA, we find that—while the overall levels of gaze coordination are not significantly different—we do find evidence for more tightly-coupled gaze between speakers and listeners at peak coordination. Our results suggest that gaze coordination is largely robust but still *somewhat* sensitive to disagreement as a conversational context. Our findings also suggest that the coordination-reducing effects of argument cannot be solely explained by a lack of understanding between speaker and listener.

5.5 Conclusion

The research area around interpersonal coordination is poised to yield unique insights into questions of human communication, interaction, and social behavior. As a field, interpersonal coordination still has immense room to grow—providing an exciting challenge to interdisciplinary researchers. Interpersonal coordination is facing an explosion of interest in recent years, making these challenges even more urgent. Here, in collaboration with various coauthors, I have presented three projects that address some of the key theoretical, methodological, and experimental issues facing the research area today. Rather than seeing each of them as separate concerns, I view development along these three dimensions—theory, methods, and experimental research—as inextricably linked to one another and to the field's continued growth.

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