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Privacy in Context: An Exploration of Factors that Shape What Privacy Means Across Time and Events

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Privacy in Context:
An Exploration of Factors that Shape What Privacy Means
Across Time and Events

A dissertation submitted in partial satisfaction

of the requirements for the degree

Doctor of Philosophy in Sociology

by

Clara K. Hanson

2022

ABSTRACT OF THE DISSERTATION

Privacy in Context:

An Exploration of Factors that Shape What Privacy Means

Across Time and Events

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Clara K. Hanson

Doctor of Philosophy in Sociology

University of California, Los Angeles, 2022

Professor Ka Yuet Liu, Chair

What is private, and among whom? The answer is always fluid because it depends on social norms, relationships, identity, and other matters of social context. This dissertation explores how 1) the concept of privacy has slowly changed over the past 50 years in a major U.S. newspaper, and 2) whether an extreme external shock, such as the Covid-19 pandemic, can change the expectations of privacy people hold.

Following an introduction, Chapter 2 takes a macro perspective to analyze differences in the language used to discuss privacy over time and across domains. It draws on news from The New York Times to ask what kinds of privacy are usually reported, and how those articles are framed. It finds that the frames used to report news about legal and social aspects of privacy are similar and have not changed much in the 50-year period I studied. In contrast, reporting about technology draws on very different frames that have shifted over time. This suggests that while concepts of digital privacy have evolved over the past three decades, the social concept of privacy in other domains is quite stable. This research also poses the theory that the stark

differences in frames leads to more transactional, less relational concepts of technological privacy.

While Chapter 2 shows discourse about privacy is largely stable, an immensely impactful social event may shift public opinion quickly. High-profile efforts to use data to combat the Covid-19 pandemic — for example, via digital contact tracing — could lead people to accept less privacy. In Chapters 3 and 4, I consider how perceptions of the pandemic affected the privacy preferences people held.

Chapter 3 draws on an ego-centered experiment to test whether relationship-centered messages about the risks of the pandemic cause people to expect less privacy. I find even though these messages do not directly discuss data or privacy, they do lower respondent expectations of privacy in some circumstances. I also conduct correlational analysis of the data to understand how attitudinal and demographic traits relate to differences in privacy expectations. This chapter suggests that more directive messaging and privacy safeguards may be needed to prevent the unnecessary erosion of privacy during times of emergency.

Chapter 4 addresses an unanswered question from Chapter 3: do people accept less privacy altruistically, or does thinking of others alter expectations of risk that then inform self-motivated behavior? I draw on survey data collected over the course of the first year of the Covid-19 pandemic to explore whether privacy preferences are better predicted by personal expectations of risk or social signals about risk. I find both factors are important predictors of privacy preferences, suggesting that privacy preferences may change during emergencies both due to self-motivated and other-regarding behavior. However, this analysis also finds evidence of a contrarian effect, suggesting that using social influence as a mechanism to affect privacy preferences can backfire.

Overall, this dissertation contributes to theory about privacy in two ways. First, it applies computational techniques to analyze the meaning of privacy across domains and over time. This contributes substantive context to the study of privacy, which is typically constrained to analyzing limited periods and contexts. Second, it tests whether sociological theories — such as social influence and network cognition — affect privacy preferences. It strengthens our understanding of privacy by improving our explanations and by studying these mechanisms at a socially important time. Finally, it contributes to the field of public health by considering the mechanisms that inform privacy preferences compared to other health behaviors. As public health develops digital surveillance methods, understanding privacy as a health-related behavior is useful.

The dissertation of Clara K. Hanson is approved.

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ACKNOWLEDGEMENTS

Earning this PhD is a dream I am amazed to attain. I first learned about academic research as an undergraduate student. Like many people who enter this field, I questioned why things are the way they are and had not found convincing answers. Understanding how our perceptions, behaviors, and opportunities are socially produced felt like learning a secret that unlocked the world. Pursuing sociological research has been equal parts exciting and overwhelming. In it, I found ideas and ways of seeing the world that finally made sense (and that, frankly, blew my mind). However, I also struggled with imposter syndrome as I adopted new methods and realized how challenging it is to produce novel research. For this reason, I am deeply grateful for the people who have listened to me, supported me, helped me grow, and helped me maintain perspective.

I am so lucky to call Ka Yuet Liu my advisor. She dedicated so much time to my intellectual and professional growth through regular meetings and detailed feedback on my work. Her feedback consistently strengthened my ideas, research design, and drafts. She ensured I had the resources to tackle my projects, be it software for text analysis or funding to conduct original surveys. She helped me be pragmatic with my time and supported me as I worked toward my own professional goals. She encouraged me to pick up new methods and pursue interesting ideas. It is difficult to completely describe how instrumental Ka is to my intellectual growth. I am eternally grateful for her knowledge, support, and guidance.

This dissertation includes work I co-authored with Ka. Chapter Three is a version of Hanson & Liu (2022) "Think about your friends and family: The disparate impacts of relationship-centered messages on privacy concerns, protective health behavior, and vaccination against Covid-19." *PLOS ONE*. Chapter Four is a version of a co-authored manuscript in

preparation for publication. For both of these chapters, Ka provided research funding, helped me develop the ideas, and provided feedback on the survey design, analysis, and written drafts.

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I was lucky to spend my final three summers working outside of academia, and am extremely grateful for the mentors who showed me the many ways my work could have impact beyond academia. I am so thankful to Sarah Ouwayda, who gave me my first opportunity to apply my computational skills to real-world problems at Google. I was honored to work for Alondra Nelson at the Social Science Research Council, and grateful to her for the opportunity to

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Hanson, Clara, Jesse Anderton, Samuel F. Way, Ian Anderson, Scott Wolf, & Alice Wang. 2022. "Time after Time: Longitudinal Trends in Nostalgic Listening." *Proceedings of the Sixteenth International AAAI Conference on Web and Social Media*.

CONFERENCE PRESENTATIONS

- International AAAI Conference on Web and Social Media, 2022. "Time after Time: Longitudinal Trends in Nostalgic Listening"
- American Sociological Association Annual Meeting, 2020. "Whose Privacy? How "User" Obscures Context and Weakens Messages About Digital Privacy"
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CHAPTER ONE: INTRODUCTION

What makes us feel like our privacy has been violated? Often, feelings of privacy are related not only to *what* information is shared, but also which actors are involved, how information is distributed, and how information is used (Anthony, Campos-Castillo, & Horne, 2017). Privacy is hard to define in a way that applies to the many kinds of privacy there are, while also being analytically useful (Kasper, 2005; Tavani, 2007). For example, privacy can mean control over personal information, control over one's body, or having solitude. Some theories conceptualize privacy as something that is inherent in particular contexts, and so privacy is violated as information travels from an appropriate context (e.g. a doctor visit) to one with different norms and expectations (e.g. to one's employer) (Nissenbaum, 2019; Baghai, 2012). Others emphasize that norms and contexts are co-constructed by people, and so argue that relationships among people should be the strongest focus in studies of privacy (Marwick & boyd, 2014). Thus, Solove (2010) proposed thinking of privacy as a pool of similar elements rather than one thing. Information privacy tends to be most salient in current research, but is itself contextual and related to other concepts of privacy.

To understand how different factors affect how people judge information privacy, consider where a person lives and works (see Thompson and Warzel, 2019 for further analysis). A person's home and work location can reveal information about their daily life and their social standing. It can also uniquely identify many people. This information may be freely shared among friends and family, although it may be more sensitive to share for some people (e.g. high ranking officials, activists, targets of abuse). Corporate or government actors may also store this information. A person may intentionally share their home and work with friends, or with services like Google Maps. They may also share this information unwittingly, for example, if an app on their phone records their location. A person may share their home and work locations because it is necessary and helpful (e.g. to arrange a carpool). It may also be harmful (e.g. if commuting patterns are used to stalk an estranged spouse). Other uses of this information may be more ethically ambiguous, for example, if home and office location are two of many inputs in an algorithm used to target advertisements. Under what circumstances would you want to share your home and office, and when would it violate your privacy?

This example illustrates how social factors like status, relationships, norms, and the social meaning of information affect judgments about privacy. In contrast to technical definitions that equate privacy with anonymity, sociological studies reveal the many ways social context bears on evaluations of privacy. As such, concepts of privacy evolve as capacities to observe, share, and use information change — from the invention of the portable camera at the end of the nineteenth century to the invention of the internet at the end of the twentieth. Understandings of privacy also change as social relationships among people change — for example, as the association between an elite patriarch's reputation and the actions of others in his household weakened over the twentieth century. The concept of privacy varies among different actors and within different contexts. Yet, privacy is an enduring social idea. How does a concept with such varied meaning continue to hold such importance?

This dissertation explores this topic first by studying privacy over a long period, and then over a short period of dramatic social change. First, I examine how the concept of privacy has slowly changed over the past 50 years in a major U.S. newspaper. Taking a long term and macro view of privacy shows not just how privacy changes, but also which concepts endure. Second, I examine whether an extreme external shock, the Covid-19 pandemic, changes the expectations of privacy people hold. During this time, the interdependency of health risk was highly salient as a person’s likelihood to be exposed to Covid was tied to the circumstances of others in their community. Did this affect other social expectations as well? By studying the meaning of privacy over both a short and long term, this dissertation increases our understanding of how the social meaning of privacy responds to social context.

Context of Privacy

Privacy is an old idea. A legal protection for privacy was established in the American colonies as early as 1604. “The Right to Privacy” — a legal article that defined privacy as the right to be left alone and shaped privacy case law throughout the twentieth century — was published in 1890. Over time, the meaning of privacy in U.S. culture has changed. Once a bourgeois notion of protecting a family’s reputation, we now understand privacy as an essential part of human growth and wellbeing (Igo, 2018a). For the past two decades, narratives about new technology purport that privacy as we used to know it is ending. Histories of privacy show that narratives like these are a recurring pattern (Igo, 2018a; John & Peters, 2017). The privacy people have changes in concert with the social and technical context they inhabit. Even as technologies and systems change, privacy tends to be most defined by relationships among people.

Privacy itself is neither good nor bad. It is a characteristic of social relations, but it is often interpreted through normative and moral ideas (Margulis, 2003). For example, in the United States, privacy is seen positively when it protects citizens and their freedoms, like freedom of speech, freedom of association, and freedom from unreasonable search and seizure. Privacy is seen negatively when it supports illegitimate or dubious behaviors like misuse of public office, vandalism, or lying. Sociologists tend to attend to the effects of privacy on individual people and their societies. Privacy can affect personal development, the intimacy of relationships, and interdependence among people. These micro structures affect broader social patterns like levels of social cohesion, social control, collective activity, and stratification (Kasper, 2007; Anthony et al., 2017). Both high and low levels of privacy can damage collective processes (Anthony et al., 2017). Established privacy norms can be self-perpetuating, reproducing similar expectations across groups of people regardless of the relation's normative value.

The extent to which privacy has truly changed since the advent of digital technologies has sparked increased research on privacy over the past two decades. Sociological work tends to study how new technologies affect the structures of social relationships. For example, the "context collapse" created as posts on social media platforms are broadcast to people from different contexts of a person's life does not always match the reference groups a person imagines, and can lead to different strategies of self-presentation (Marwick & boyd, 2010). Capacities to record and store many types of media, from text to video, expand the kinds of records a person may make, and the period of time actors may access those records. Information sharing is complicated by the fact that personal information is not always about just the person sharing the information. Relational information inherently reveals something about another person (Marwick & boyd, 2014; Sarigol et al., 2014), and aggregated personal data can enable inferences about others in a population (Garcia, 2017). As these systems and relational structures change, to what extent does the concept of privacy change too?

Modern privacy is further complicated by the relationships between people and institutions. Platform hosts can observe and record how people interact with the platform and other people on it, as can other institutions that gain access to this information (e.g. governments). Institutions like technology companies and governments have more control than individual people over the technological structures and policies underlying these platforms. These platforms and their algorithms shape behavior and information access (Earl, 2012; Zuboff, 2015). What institutions can observe and how they use it (i.e. the circumstances of online privacy) have far reaching implications for the circulation of news and misinformation, economic stratification, social interaction, and mass culture, in addition to capacities for expanded surveillance (Burrell & Fourcade, 2021; Fourcade & Healy, 2017; Bakshy et al., 2015; Chen et al., 2021; Nieborg & Poell, 2018). As increasingly large amounts of human data are available to serve different ends, does the concept of privacy between different kinds of actors change?

A Rapid Change in Social Context

Millions of people rapidly changed where they went and who they interacted with in response to the global spread of SARS-CoV-2. Many interventions of the Covid-19 pandemic required the cooperation of many people to be effective, such as stay home orders and vaccination programs. Community spread of the virus made salient that a given person's health outcomes were tied to the actions of others.

Having information like disease exposure, disease status, and symptoms are a critical component of an effective public health response. This information is often measured in different ways at the level of individual people. It is used to inform different kinds of interventions — from assessing level of risk for various mandates to carrying out contact tracing. While this information is useful for public health efforts, it can also be sensitive for people to share. Given the urgent threat of the pandemic and the advancement of digital technology systems, some governments and organizations had an appetite to develop new data systems (e.g. exposure notifications).

Countries varied in their systems of public health surveillance prior to the pandemic. For example, in the U.S., de-identified patient records from healthcare providers are routinely used for infectious disease control without patient consent. However, sharing identifiable records requires patient consent. De-identified hospital records were among the most important sources of data in the U.S. (CDC, 2021). A contrasting approach is that of South Korea. A law passed in response to an earlier epidemic granted the government expansive surveillance powers for public health. This includes linking medical records, banking information, phone location data, and CCTV footage. South Korea coupled this expansive surveillance power with diagnostic tests, contact tracing, and targeted closures of schools and businesses (Dyer, 2021). South Korea was more effective than most countries at containing the Covid-19 pandemic. These two cases demonstrate different approaches to balancing privacy with the public good.

Countries also varied in the technologies they developed in response to the pandemic. Digital contact tracing and exposure notification is a prominent example. The concept of this technology is to automate contact tracing by passively collecting information about who a person has been in contact with. This technology was idealized as a quicker, more accurate, scalable method for contact tracing. However, scholars were skeptical that it would be effective in practice — in part because it requires use by a high proportion of the population who must have smart phones (Cebrian, 2021). Different implementations of this technology create different privacy risks. For example, GPS is regarded as more invasive than Bluetooth, and scholars debated a centralized versus decentralized structure (Bagchi et al., 2020).

This approach to surveillance was adopted unevenly across the globe. Apps like TraceTogether in Singapore and Aarogya Setu in India were made mandatory for many citizens or to enter vital buildings. Other governments cited skepticism about the effectiveness of these apps as a reason not to develop them or discontinue their development, as in New Zealand and Norway. In the U.S., some states developed such apps, but they were not widely adopted. The most high profile approach was a collaboration between Google and Apple, but it was neither widely downloaded nor used (De Vynck & Zakrzewski, 2021).

These examples illustrate why behaviors during the Covid-19 pandemic are a useful case to understand privacy. The interdependence of risk inherent in contagious diseases may have changed the expectations people hold for themselves and their society, and so many people were motivated to change their behavior via risk and via social pressure. Information is a critical component of addressing the pandemic. However, which systems were useful and which were not, which were privacy protecting and which were privacy violating, was not always straightforward. What information people were willing to share and which public health surveillance systems they supported is a way to observe how responses to changing circumstances and beliefs inform the views of privacy people hold.

A sociological perspective is important to understanding privacy because privacy emerges through interpersonal processes. Concepts of privacy and normative judgments of its value are socially constructed. The level of privacy people have relies not just on what that person does, but also what other actors who could be observers do. Understanding the social process that shape privacy can contribute to theories in social psychology, economic sociology, and science and technology studies. It also has substantial practical implications for the design of technological systems, privacy regulation, and privacy communication.

Overview of Dissertation

Following this introduction, Chapter 2 takes a macro perspective and considers the meaning of privacy over a long period. It analyzes differences in the language used to discuss privacy over time and across domains. It draws on news from The New York Times to ask what kinds of privacy are usually reported, and the frames used to discuss those concepts. It finds that the frames used to report news about legal and social aspects of privacy are similar and have not changed much in the 50-year period I studied. In contrast, reporting about technology draws on very different frames that have shifted over time. This suggests that while concepts of digital privacy have evolved over the past three decades, the social concept of privacy in other domains is quite stable. This research also poses the theory that the stark differences in frames leads to more transactional, less relational concepts of technological privacy.

While Chapter 2 shows discourse about privacy is largely stable, one may expect immensely impactful social events to shift public opinion quickly. In Chapters 3 and 4, I consider how perceptions of the pandemic affected the privacy preferences people held.

Chapter 3 draws on an ego-centered experiment to test whether relationship-centered messages about the risks of the pandemic cause people to have lower expectations of privacy. It finds that even though these messages do not directly discuss data or privacy, they do lower respondent expectations of privacy in some circumstances. I also conduct a correlational analysis to explore how social traits relate to differences in privacy preferences. This chapter suggests that more directive messaging and privacy safeguards may be needed to prevent the unnecessary erosion of privacy during times of emergency.

Chapter 4 addresses an unanswered question from Chapter 3: if people accept less privacy when they consider risks of the Covid-19 to other people, is it due to rationality or altruism? That is, does thinking of others alter a person's perception of risk which then increases their willingness to share information, or does thinking of others encourage people to act for the benefit of others? I draw on survey data collected over the course of the first year of the Covid-

19 pandemic to explore whether privacy preferences are better predicted by personal expectations of risk or social signals about risk. I find both factors are important predictors of privacy preferences, suggesting that privacy preferences may change during emergencies both due to self-motivated and other-regarding behavior. However, this analysis also finds evidence of a contrarian effect, suggesting that using social influence as a mechanism to shape privacy preferences can backfire.

Chapter 5, my conclusion, summarizes the findings of the empirical chapters. I connect the findings from these chapters to the theoretical motivation to conduct this work — understanding how and when notions of and expectations for privacy change. Finally, I discuss the implications of this work.

Significance

Overall, this dissertation contributes to theory about privacy in two ways. First, it applies computational techniques to analyze the meaning of privacy across domains and over time. This contributes substantive context to the study of privacy, which is typically constrained to analyzing limited periods and contexts. Second, this dissertation tests whether sociological theories — especially those on social influence and network cognition — affect privacy preferences. It strengthens our understanding of privacy not only by improving our explanations, but also by studying these mechanisms at a socially important time. Finally, it contributes to the field of public health by considering the mechanisms that inform privacy preferences compared to other health behaviors. As public health develops digital surveillance methods, understanding privacy as a health-related behavior is useful.

CHAPTER TWO: WHAT IS PRIVACY? SHIFTING MEANINGS OF PRIVACY IN NEWS DISCOURSE OVER HALF A CENTURY

Introduction

A person's culture and circumstances affect what they understand privacy to be, and when they perceive it as desirable or undesirable, priceless or trivial. For example, having privacy can support personal development, intimate relationships, and social cohesion; but it can also conceal violence and manipulation. Lacking privacy can increase discrimination, social control, and exacerbate stigma, but it can also enable the enforcement of laws and facilitate commerce. Evaluating privacy is a social process, as the level of privacy one has depends on others, and the judgments one makes relies on cultural ideas about particular relationships and actors.

Privacy is contextual. What to share and what to keep private often depends on the relationship between actors, the kind of information being shared, and how that information will be used. Digital technology creates new relationships between people and institutions, new ways to infer information, and new uses for that information. Digital technologies often monetize the information they collect. Potentially, this connects privacy and market concepts in ways other concepts of privacy have not. Yet who knows what and how they use what they know is often invisible to people who are observed by technology. Understanding what privacy means today is particularly important as digital technologies proliferate in more contexts of social life, and may require a reevaluation of what privacy means, when it is valued, and why.

Despite widespread agreement that the meaning of privacy is highly contextual, many scholars still work toward developing a single definition of privacy. Perhaps this is because a single definition of privacy would clarify the concept and enable policies and technologies that better protect privacy. Smith, Dinev, & Xu (2011) find many normative and theoretical studies of privacy, but little empirical work to test those ideas. Empirical studies that do examine what privacy means tend to focus on particular contexts of privacy. Few studies take empirical approaches to understand how privacy is defined across contexts. Yet empirical work that clarifies whether the meaning of privacy varies by context can consider whether privacy is treated as a single concept or as multiple concepts in the interactions that produce its meaning.

In this study, I ask: 'Is privacy treated as a single concept or multiple concepts?' using news text about privacy over a 50-year period. I address this question in three ways. First, I examine what contexts of privacy are discussed most often using a structural topic model. Second, I consider whether the prevalence of sanctity and transaction language changed over the course of the corpus. Third, I explore how sanctity and transaction language varies by topic. These results show privacy discourse about technology and the law are more connected than either is to discourse about day-to-day life, but technology is framed very differently than the law or day-to-day life. These results suggest privacy is written about as several distinct subjects.

Some narratives describe privacy as a thing people once had, that is suddenly disappearing with the advent of new technologies. This study supports a growing body of work that argues privacy is an idea that changes as societies reckon with new systems, new technologies, and new ideas (Igo, 2018a; John & Peters, 2017). This study adds that the frames present in privacy discourse tend to change as new topics of privacy are introduced. Although the framing of privacy can change over time, there is stability in the content of privacy discourse.

Literature

A Brief History of Types of Privacy Concerns in the U.S.

Many of today's key privacy concerns are not new; privacy has long been understood as an interpersonal, legal, and technological concept in the United States.

What people do and say shape what privacy is and how much of it people have. Homes and the domestic sphere are often treated as uniquely private spaces; legal protection for privacy in one's home was established in the U.S. as early as 1604 by *Semayne's case* (Solove, 2006). Very old, western notions of interpersonal privacy emphasize harm to a person's reputation and embarrassment. Relatively newer notions emphasize how space and solitude can foster personal growth. Historian Sarah Igo (2018a) uses the invention of photography and mass-media to illustrate the former, and the popularization of separate bedrooms through Cold War era suburban architecture to demonstrate the latter. Expectations of privacy in day-to-day life are difficult to observe, but they have long affected what is deemed public or private, right or wrong.

Judicial decisions and legislation codify what privacy is and how it is protected in the U.S. Warren & Brandeis's influential 1890 law review article, 'The Right to Privacy,' introduced the idea that privacy is 'the right to be left alone.' Legal scholars have refined this definition in the centuries since (Solove, 2006; Gormley, 1992). Beginning in the mid-twentieth century, a series of Supreme Court cases defined privacy rights in the U.S. — *Katz v. United States* 1967 defined standard for lawful search and seizure, *Griswold v. Connecticut* 1965 overturned laws criminalizing birth control, *Stanley v. Georgia* 1969 overturned laws criminalizing the possession of pornography, *Lawrence v. Texas* 2003 overturned laws criminalizing sodomy, and most famously, *Roe v. Wade* 1973 established a right to privacy that protected the decision to have an abortion. Privacy became 'good politics' in the 1970s, and legislation like the Privacy Act of 1974 and the Health Insurance Portability and Accountability Act of 1996 protected particular forms of privacy. Other legislation like the USA PATRIOT Act of 2001 restricted privacy (Igo, 2018a; Solove, 2006). Though *Dobbs v. Jackson Women's Health Organization* 2022 overruled *Roe v. Wade* 1973, the line of reasoning has been politically influential even as it is no longer binding precedent in case law. The legal system affects many kinds of privacy, and has been the primary avenue for defining and creating entitlements to privacy for over a century.

Privacy concerns about communication technology and records also have a long history. A key concern in the eighteenth-century U.S. was protecting mail from being opened and read by unintended recipients, and similar concerns persisted as technologies to tap telegraphs and telephones were introduced shortly after each was invented (Solove, 2006; Igo, 2018a). New federal records systems sparked controversy over what they would contain and how they would be used, from the introduction of the Census in 1790 to social security numbers in 1935 (Solove, 2006; Igo, 2018a). These concerns are echoed in modern concerns about digital technology and databases, which began as concerns about computers and data banks in the 1970s (Igo, 2018a; Allen, 2001).

Privacy takes on different meanings in each of these contexts: it is a right or an entitlement in the legal context, a state of access or isolation in a social context, and a level of control over information in an information systems context (Smith, Dinev, & Xu, 2011). Though these contexts are distinct, they often overlap as norms, laws, and technologies mutually shape one another.

Is Privacy Contextual or Comprehensive?

As the history of privacy shows, there are many contexts in which one's privacy can be violated. In addition, there are many components of privacy within these contexts, for example: who shares information, who receives information, who the information is about, the topic of the information, and how the information was learned (Nissenbaum, 2019; Marx, 1998). Privacy is not static, but instead varies across particular encounters (Andersen et al., 2018), over time (Nissenbaum, 2001; Viseu, Clement, & Aspinall, 2004), and across groups and cultures (Martin, 2012). This complexity makes the meaning of privacy difficult to define (Acquisti, Taylor, & Wagman, 2016). Legal scholar Daniel Solove (2010) argues privacy should be treated as a pool of similar elements rather than one concept.

Yet scholars work toward comprehensive definitions of privacy (e.g. Tavani, 2007; Moore, 2008). Privacy affects the lives of people and the wellbeing of societies (Anthony, Campos-Castillo, & Horne, 2017) and is prohibitively difficult for individual people to maintain (Acquisti, Brandimarte, Lowenstein, 2020; Barocas & Levy, 2020). If possible, a comprehensive definition of privacy would enable clearer comparisons within privacy research and more targeted policymaking. There may be unrecognized similarities across seemingly distinct contexts. As historian Sarah Igo (2020b) observes, public backlash to privacy violations tends to repeat similar kinds of tensions across topics over time. Though theorists work toward defining privacy, little empirical work addresses whether privacy is treated as a single concept in practice.

Tracing the Moral Frameworks of Privacy

If something is sacred, it is seen as too valuable to be contaminated, disturbed, or otherwise interfered with. Many notions of privacy are rooted in these ideas of sanctity and purity, beginning with 'The Right to Privacy' (Warren and Brandeis, 1890). The influential 1890 paper emphasized privacy as a matter of 'inviolate personality' rather than a matter of property (Solove, 2002). The idea that privacy is a moral right, not a kind of property, endures today (Alfino & Mayes, 2003). Legal scholars emphasize that liberty is protected by the sanctity of private spaces (Whitman, 2003), and the importance of granting privacy to preserve human dignity (Solove, 2002). Concepts that frame privacy as something inviolable, a moral right, sacrosanct, and about preserving dignity all draw on the moral logic of sanctity (Graham, Haidt, & Nosek, 2009, p. 1044).

Contemporary privacy concern tends to focus on digital platforms. Digital platforms are markets in which data is gathered from consumers, and that data is used to target advertisements (Fourcade & Healy, 2017; Zuboff, 2018). This could create a moral conflict, as Western cultures understand treating sacred things (e.g. sex, human life) as market goods to be morally wrong (Healy & Krawiec, 2017). Yet strategic rhetoric (Quinn, 2008) or obfuscating transactions (Schilke & Rossman, 2018) can inhibit condemnation and promote acceptance of otherwise immoral exchanges. Barbara Kiviat (2019, 2021) finds some public acceptance of treating data privacy like a market. When data transactions were judged by respondents as a fair exchange, they were more likely to accept the structure of the market overall. Marketization could decrease the moralization of privacy and decrease understanding privacy as something sacred.

Frames are a useful way to study cultural concepts of privacy. Frames simplify complex processes by making some aspects of reality more salient than others (Goffman, 1974; Entman, 1993). Those salient aspects promote particular ways of defining problems, interpreting causes, and evaluating morality. Framing should be especially important for privacy, because emphasizing different aspects of a situation changes how people evaluate privacy risk (Tsai et al., 2010; Goldfarb & Tucker, 2011).

Past studies of privacy in news discourse reveal particular ways privacy is framed. From 1990 –2003, descriptions of invasions of privacy focused on actors that were more unseen, unknown, and ongoing, alongside the mass adoption of home computers (Kasper, 2005). From 1990–2012, 'the end of privacy' was a common frame across a broad range of privacy violations

(John & Peters, 2017). Connor & Doan (2021) find evidence that reporting on a similar surveillance technology was more moralized and threatening when the technology was used by government actors than when used by corporate actors. How privacy is framed in news varies in European contexts, from a privacy-as-control framework in Flemish newspapers (De Wolf & Joye, 2019) to a focus on EU legislation in Polish newspapers (Wojtkowski et al., 2020).

Though these studies evaluate what aspects of privacy news emphasizes, they are bound to particular kinds of privacy at particular times. This approach may miss patterns in how news frames privacy across different contexts. For example, focusing on digital privacy excludes discussion of privacy in analog life. In what follows, I use quantitative text analysis to analyze 34,236 articles about privacy published between 1970–2020. I evaluate which privacy topics are often reported on, and how often they are framed in terms of sanctity versus in terms of transactionality. By doing so, I evaluate whether privacy topics draw from the same frames, which would suggest a consistent understanding of the meaning of privacy across topics. If privacy topics draw from different frames, it would suggest more context-driven understandings of the meaning of privacy.

Data & Methods

Dataset

Data for this research consists of full-text articles about privacy spanning 50 years published in the New York Times. I identified all articles containing the word *privacy* published between 1 January 1970 to 31 December 2020 using The New York Times's Article Search API. I exclude non-text article types (e.g. videos) and irrelevant article types (e.g. schedules, obituaries). I collected full text for 71.29% of all articles. Most articles from 1980 are not digitized, and so this analysis excludes the year 1980. Missing articles are otherwise distributed evenly throughout the period (see Figure 2.1A). I removed duplicate paragraphs by measuring how similar paragraphs are with Jaccard similarity on 2-character n-grams. Paragraphs with scores equal to or greater than 0.80 were counted as duplicates, and only the earliest paragraph was kept. This method ensured identical and nearly identical paragraphs did not over represent the correlation between particular words. The final corpus contains 34,236 articles and 54,404 paragraphs containing the word privacy.

Sanctity and Transactionality

I use two dictionary-based approaches to identify sanctity and transaction language. Given that frames manifest in text via the presence or absence of key words and phrases (Entman, 1993), dictionary approaches are appropriate and efficient for detecting frames at a large scale. To detect sanctity, I use the positive-valence sanctity list from the moral foundations dictionary 2.0 (Frimer et al., 2019; Frimer, 2020). This dictionary builds on existing work in moral foundations theory by adding more words that convey moral meaning (Haidt & Joseph, 2004; Graham et al., 2009).

To detect transactionality, I use a list of words related to market transactions. There is no commonly accepted dictionary to measure transactional language in text. This study introduces a list of terms associated with transactions and their synonyms, the Transactional Language Dictionary. Words with additional meanings that do not correspond to transactions are excluded. A complete list of these terms is available in Figure 2.2A.

This analysis is interested in the presence or absence of sanctity and transactionality frames, and so I code sanctity and transactionality into binary variables.

Topics in Text

To understand the contexts discussed in news discourse about privacy, I use a structural topic model (Roberts, Stewart, & Tingley, 2019). Like other topic models, structural topic models capture the latent topics of a corpus of documents using probabilistic methods to estimate topics from the distribution of words across documents. Topics are represented as a mixture of words, where each word has some probability of belonging to that topic. Documents are represented as a mixture of topics, where each document can be composed of multiple topics. Topic modeling allows for the ambiguity of language, where the same word may be used to discuss many topics, and multiple topics may be discussed in the same document. Unlike other kinds of topic models, structural topic models allow for the incorporation of non-text covariates, such as publication date or aspects of authorship. This allows exploration of the association between text and context, but also tends to result in higher-quality topics (Roberts, Stewart, & Airoldi, 2016).

I train a structural topic model using paragraphs that contain the word privacy. Both very long and very short documents can result in incoherent topics, and so the focused style of news paragraphs is a good fit for topic modeling. To improve modeling, I processed the text in the following ways: stopwords, numbers, punctuation, and words shorter than 3 characters were removed; the remaining words were lemmatized with the Wordnet lemmatizer and converted to lowercase; among the remaining word-tokens, those appearing in only one document were removed from the corpus. Nine paragraphs were empty due to text processing, and were removed from the corpus. Documents were represented with a count matrix.

I selected a structural topic model with 43 topics, and included controls for publication year and document type (e.g. news, op-ed, letter). There is no single statistical method to determine how many topics (k) best represent a corpus. I evaluated the topics created by models with between 5–80 topics, and noted whether increasing k resulted in new and informative topics, or redundant or uninformative topics. Statistical estimation somewhat validates my selection of k=43 topics. Held-out likelihood, which measures how well a topic model generalizes to documents it was not trained with, is similar for k between 20–80. All models were trained using spectral initialization and a train-test split to improve the robustness of model estimation. The topic model outputs a vector for each document that estimates topic proportions and sums to 1.

To visualize the results of this model, I use a correlation network. It represents topics as nodes, and the correlation between topics (a measure of how often they co-occur in the same paragraph) as weighted edges. All topics with a correlation above 0.01 are connected by an edge, and edge weight corresponds to the strength of the correlation. To evaluate patterns of correlation among the topics, I used greedy modularity maximization to detect cluster structure. Modularity measures how connected nodes within clusters are compared to how connected they would be if edges formed randomly. I also used betweenness centrality to consider patterns of relationships among nodes. Betweenness centrality measures how often a node connects unconnected nodes. Thus, betweenness centrality identifies topics that serve as bridges between otherwise unconnected privacy topics.

To visualize the occurrence of sanctity and transactional language over time, I partition articles into evenly sized, chronological bins because articles are unevenly distributed over time.

Results

Topic Model Results: Central Themes in Privacy Discourse

The topic model identifies topics that primarily fit into one of three categories: legal approaches to privacy, technology and privacy, or privacy in day-to-day life. These groups are broadly consistent with scholarly characterization of privacy topics. Figure 2.1 shows an overview of these topics. The strongest correlation in the graph is 0.25. The clusters shown have a modularity score of 0.546, indicating a strong cluster structure in the network. This analysis focuses on the substantive topics the model identifies, and excludes topics that capture journalistic norms or spurious correlations. For a full overview of the topic model, see Table 2.1A.

Many topics in the privacy and technology cluster (white nodes) discuss digital privacy but focus on different aspects. ‘Privacy of Technologies’ focuses on specific technologies and their capabilities (e.g. cameras, sensors, algorithms), ‘Comms Privacy’ discusses the content shared in communications technology, and ‘Tech Companies’ focuses on the major corporations producing these technologies (e.g. Google, Facebook). ‘Internet Regulation’ and ‘European Privacy Law’ focus on potential policy approaches to regulate these companies and their technologies in the E.U. ‘Mass Surveillance’ discusses use of digital technology by the government of the United States for surveillance. Other topics identify ways of talking about technology: ‘Online Privacy Tools’ is a didactic topic about how to use online privacy tools, while ‘Problematizing Digital’ uses a conversational tone to discuss what digital privacy means, how it could affect readers, and what it may look like in the future. ‘References to Orwell’ represents references to George Orwell and the dystopian novel *Nineteen Eighty-Four*.

The topics in the technology cluster reflect components of privacy violation: who receives information (Tech Companies, Mass Surveillance), the topic of information (Comms Privacy), and how the information was learned (Privacy of Technologies). Though no topics primarily focus on who shares information or who information is about, other topics explain legal (Internet Regulation, European Privacy Law) and technical (Online Privacy Tools) interventions.

The topics in the legal privacy cluster (light grey nodes) correspond to different approaches to governing privacy. ‘Case Law’ is the largest topic in the corpus, and best characterizes nearly 7% of articles in the corpus. It focuses on the precedents set by case law that regulates sex and sexuality, including *Griswold v. Connecticut*, *Roe v. Wade*, and *Bowers v. Hardwick*. Case law is likely a large topic in this corpus because a series of influential legal decisions on privacy were established beginning in the late 1960s and lasting through the new millennium. In addition, ‘Invasion Litigation’ focuses on lawsuits related to the invasion of privacy, and ‘Fourth Amendment’ discusses protection from unreasonable searches and seizures granted by the Fourth Amendment. Three additional topics focus on policy making: ‘Presidents,’ ‘The Senate,’ and ‘Privacy Legislation.’ In contrast to the other topics, ‘Medical Privacy’ and ‘Diagnostics’ focus on specific contexts of privacy that have strong legal protections.

The topics in the day-to-day life cluster (medium grey nodes) reflect both contexts and components of privacy. ‘Relational Privacy’ is the second largest topic in the corpus, and best characterizes 6% of paragraphs. It represents the ways people have, seek, wish for, or don’t need privacy from other people and institutions. It is not focused on a particular context, but is instead focused on how relationships among actors determine privacy. Similarly, ‘Narratives & Context’ captures first person accounts describing contexts that create or preclude privacy. In contrast, four topics focus on the same specific context: homes. ‘Home Exteriors’ and ‘Home Interiors’ focus on the physical structures and social expectations related to homes. ‘In Your Own Home’ captures different ways of saying ‘in the privacy of your own home,’ a phrase that emphasizes that homes are exceptional, private spaces. ‘Sex in Close Quarters’ focuses on gender and privacy expectations in settlements, such as military camps and refugee camps. A third set of topics discuss artistic works about privacy, and the role of privacy in the creative process: ‘Privacy & Literature,’ ‘Art & Nature,’ and ‘Performance.’ In contrast to the mechanism-focused law cluster and the components-focused technology cluster, the day-to-day life cluster captures ways of talking about everyday aspects of privacy in relationships and spaces.

Interestingly, the model does not identify substantial topics about privacy and markets. ‘Banking & Commerce’ and ‘Wealth’ (dark grey nodes), focus on finance. However, they best characterize very few paragraphs in the corpus — less than 1% combined. They focus on privacy afforded to those with very high levels of wealth. ‘Tech Companies’ does concentrate on the corporations that produce technologies, but its content focuses primarily on litigation, regulation, and executive leadership rather than transactions with consumers. Although tensions between commerce and privacy predate digital technology, this analysis does not find substantial topics about privacy and commerce. This indicates there is no strong precedent in news discourse for talking explicitly about the relationship between privacy and markets.

The clusters shown in Figure 2.1 have a modularity score of 0.546, indicating a strong cluster structure. Topics in the same cluster are more likely to be discussed in the same paragraph. Topics in different clusters tend not to be positively correlated; they’re not any more likely, and may be less likely, to be discussed together. Figure 2.1 suggests privacy topics are not discussed as wholly unrelated ideas, but instead are discussed as different clusters of related ideas.

Some topics are not connected, but share a node in common. Common nodes that bridge unconnected topics reveal the shared conceptual logic of unconnected nodes. For example, there is no connection between 'Case Law' and 'European Privacy Law,' but both topics are connected to 'Privacy Legislation.' These bridges help resolve the conflicting idea that privacy is both highly context dependent and a unified idea.

Topics that serve as logical bridges show how ideas about privacy are related, even in otherwise unconnected topics. ‘Privacy Legislation’ has the highest betweenness centrality (0.194), and connects the technology cluster with the legal cluster. Many of the connections between ‘Privacy Legislation’ and the nodes it connects to are relatively strong, and it is connected to several topics in the two clusters it bridges. This indicates ‘Privacy Legislation’ is a relatively strong logical bridge. ‘Sex in Close Quarters’ has the second highest betweenness centrality (0.175), and connects the legal cluster to the day-to-day life cluster. However, it is a relatively weaker logical bridge. It connects to two topics in the legal cluster, and the edge strength is very weak. Finally, ‘Problematizing Digital’ (0.123) has the third highest betweenness centrality. It connects topics in the day-to-day life cluster with topics in the technology cluster. It is also a relatively weak bridge. No single topic connects the three largest clusters. Together, these measures indicate that law and technology tend to be treated as related more often than day-to-day life and either other cluster, despite connections between all three clusters. It may seem logical to connect technology to legislation, but it may seem like a much bigger leap to connect day-to-day life with technology or legislation because they are not as often discussed together.

Figure 2.2 shows that Legal and Day-to-Day life discourse are not being replaced by Technology discourse, but Technology has become a much larger focus of privacy discourse. Between 1970–1990, privacy articles primarily focused on Legal and Day-to-Day Life topics of privacy. The number of articles about technology began to increase steeply in the mid-1990s. By 2010, Technology articles consistently outnumbered Legal and Day-to-Day life articles. Though the proportion of technology articles in privacy discourse increased significantly, the total number of Legal or Day-to-Day Life articles did not decrease. Instead, they decreased in proportion to Technology articles as the number of Technology articles increased.

Measuring Sanctity and Transactionality: Changes in the Framing of Privacy Over Time

The results of the topic model show the content of privacy discourse has changed over time. In this section, I evaluate whether the prevalence of two frames used to discuss privacy — sanctity and transactionality — vary over time and by topic.

Figure 2.3 shows transactional language in privacy discourse increased, and sanctity language decreased. Transactional language occurred in 12.15% of articles in 1970, and 22.29% of articles in 2000, an increase of 83.42%. Use of transactional language was high but uneven in the years following 2000. In contrast, sanctity language steadily decreased. Sanctity language occurred in 9.37% of articles in 1970, and 5.75% of articles in 2020, a decrease of 38.62%. Though these frames follow opposite trends over time, there is limited evidence transactional language is replacing sanctity language. The correlation between the occurrence of transactional and sanctity language in paragraphs is relatively weak $r(53{,}368) = -0.033$, $p = 0.000$. These results suggest news discourse about privacy has become more transactional and less sanctified over time, but that increasing use of transactional language may not decrease use of sanctity language.

The prevalence of transactional and sanctity frames varies by topic, shown in Figure 2.4. Sanctity language is used less often, but varies significantly by topic. It is most prevalent in Day-to-Day Life topics, appearing in 13.43% of paragraphs, and least common in Technology topics, appearing in 2.06% of paragraphs.

While transactional language occurs evenly in Day-to-Day Life discourse, it occurs more often than sanctity language in Legal and Technology topics. The difference is smaller in Legal topics — 11.52% of paragraphs contain transactional language, compared to 7.74% of paragraphs that contain sanctity language. The difference is much larger within Technology topics — 54.6% of paragraphs contain transactional language, compared to 2.06% that contain sanctity language.

Privacy topics use sanctity and transactional language at different rates. This suggests frames do vary by privacy topic. Discourse about Day-to-Day life emphasizes the transactional and sacred aspects of privacy evenly across paragraphs. In contrast, discourse about the law emphasizes transactional aspects of privacy somewhat more than sacred aspects. In technology discourse, transactionality is extremely salient, and sacredness is not.

The most frequently used terms for each measure convey what these frames emphasize. The most common transactional terms in the corpus are: user*, consumer*, customer*, market*, trade, deal*, commerc*, buy*, obtain*, and price*. The first three words emphasize transactionality through the way they refer to people (users, consumers, customers). The most common sanctity terms are: body, dignity, marriage, food, married, church, religious, religion, and clean. These words emphasize religious institutions (church, marriage), as well as more general concepts (dignity, clean). Regardless of whether these terms are used literally or metaphorically in each paragraph, the measures capture what aspects of a topic are being made salient. Digital platforms are markets, but they are also part of social life. That most Technology paragraphs use transactional language means that discourse, either by reporting on technology as a business or by emphasizing transactional aspects of technology, makes transactionality a dominant way of thinking about digital privacy.

Figure 2.5 suggests corpus-wide changes in the proportion of sanctity and transaction language are driven by the composition of topics in the corpus, and not by changes in language across topics. There is no significant change in sanctity language over time in any cluster, and there is no significant change in transactional language in Day-to-Day Life discourse. Transactional language increased in Legal discourse, but the correlation between time and transactional language is very weak ($r(5337) = 0.043$, $p = 0.002$). Transactional language decreased in Technology discourse, though the correlation is weak as well ($r(5337) = -0.115$, $p = 0.000$). Between April 1976 – August 2000, 66.29% of paragraphs about Technology used at least one transactional word; by 2020, only 38.76% did. Despite the meaningful decrease of transactional language in Technology discourse, the overall amount of transactional language in the corpus increased as the amount of Technology discourse increased.

The same trend likely explains the decrease in sanctity language in the corpus overall. Day-to-Day Life and Legal discourse have not decreased in amount over time, but they have not grown at the same rate as Technology discourse. Sanctity language is more prevalent in Day-to-Day Life and Legal discourse than it is in Technology discourse. As technology makes up a larger proportion of privacy discourse, the proportion of sanctity language decreases.

There is no strong evidence to suggest a spillover effect in the frames used by some topics to others. A spillover effect would occur if the emergence of the Technology cluster in privacy discourse resulted in increases in transactional language and decreases in sanctity language in other topics. The prevalence of frames in Day-to-Day life discourse did not change. Transactional language in the legal cluster increased a small amount, but there is not enough evidence in this analysis to conclude the increase was caused by the emergence of Technology discourse. The stability of sanctity and transactional language suggests that, in contrast to the idea that the meaning of privacy is constantly changing, common frames used to discuss privacy are stable within established clusters of privacy discourse.

New topics, however, may change the presence of frames in privacy discourse. In this analysis, topics that intersect law and technology emerged ('Internet Regulation,' 'European Privacy Law,' and 'Mass Surveillance'). These techno-legal topics are grouped in the Technology cluster, not the legal cluster. This indicates they are discussed with other technology topics more often than with established legal topics. While there is limited evidence Technology topics changed established legal discourse, it is possible new legal topics emerged that conform more closely to the framing of technology discourse.

Discussion

The clusters of topics produced by the topic model reflect the primary subjects studied in privacy literature, but the topics within those clusters reflect different kinds of theories about privacy. Topics in the Technology cluster focus on different elements of context that create or violate privacy, such as how information is gathered, how information is transmitted, and who receives information. These elements are like Helen Nissenbaum’s (2019) work on contextual integrity. However, there are no substantive topics about who shares information, or who information is about, two key elements of Nissenbaum’s theory. 'User,' 'customer,' and 'consumer' are the most common transactional words in the corpus, which suggests that instead of discussing the stakes of privacy for people as a focal topic, most topics discuss people in a general way that frames them as part of a transaction. This is a meaningful omission, as people who use technology tend to have less information about their privacy than the platforms that structure it (Acquisti et al., 2016; Cooke, 2020).

Unlike technology, topics about privacy and the law focus on different mechanisms for regulating privacy, such as case law and the Fourth Amendment. Legal theory debates different philosophies for defining privacy and privacy violation (Benn, 1971; Parent, 1983). Privacy law in the U.S. regulates privacy by industry rather than by information sharing practices more generally, as the E.U. does. Some U.S. laws do reflect different philosophies for regulating privacy (Gormley, 1992). While legal theory may be discussed incidentally, legal privacy discourse is structured by the fragmented privacy laws that do exist rather than by ideas about what could exist.

Discourse about privacy in day-to-day life most reflects classical social theory about privacy (Goffman, 1963a; Goffman, 1963b; Moore, 1984). It acknowledges social construction indirectly, by discussing the ways privacy is co-created through physical spaces and through relationships. In contrast to technology discourse, it tends to center the perspectives of people who could share information, who could be the subject of information, and who experience privacy. It is not focused on a particular industry. Some topics within it are truly latent, identifying ways to discuss privacy rather than particular contexts or components of privacy. Privacy discourse about day-to-day life centers people, their spaces, and the groups they belong to.

This analysis provides empirical support for the notion that concepts of privacy are so contextual that privacy is difficult to capture with a single definition (Solove, 2010; Baghai, 2012; Acquisti et al., 2016). Correlations within the topic model show that technology and legal discourse are more often connected through discourse than either is with day-to-day life. It may be more intuitive to connect the ways privacy is encoded in specific technologies and regulated through laws than to connect either to the ambiguous ways people think about their own privacy.

However, legal and technological privacy discourses draw from sanctity and transactional frames at different rates. The salience of sanctity and transactionality are similar in news about the law and news about day-to-day life. In contrast, transactionality is very salient in technology discourse, and sanctity is rare. This indicates privacy discourse about technology, the law, and day-to-day life tend to be discussed as distinct contexts, rather than related contexts.

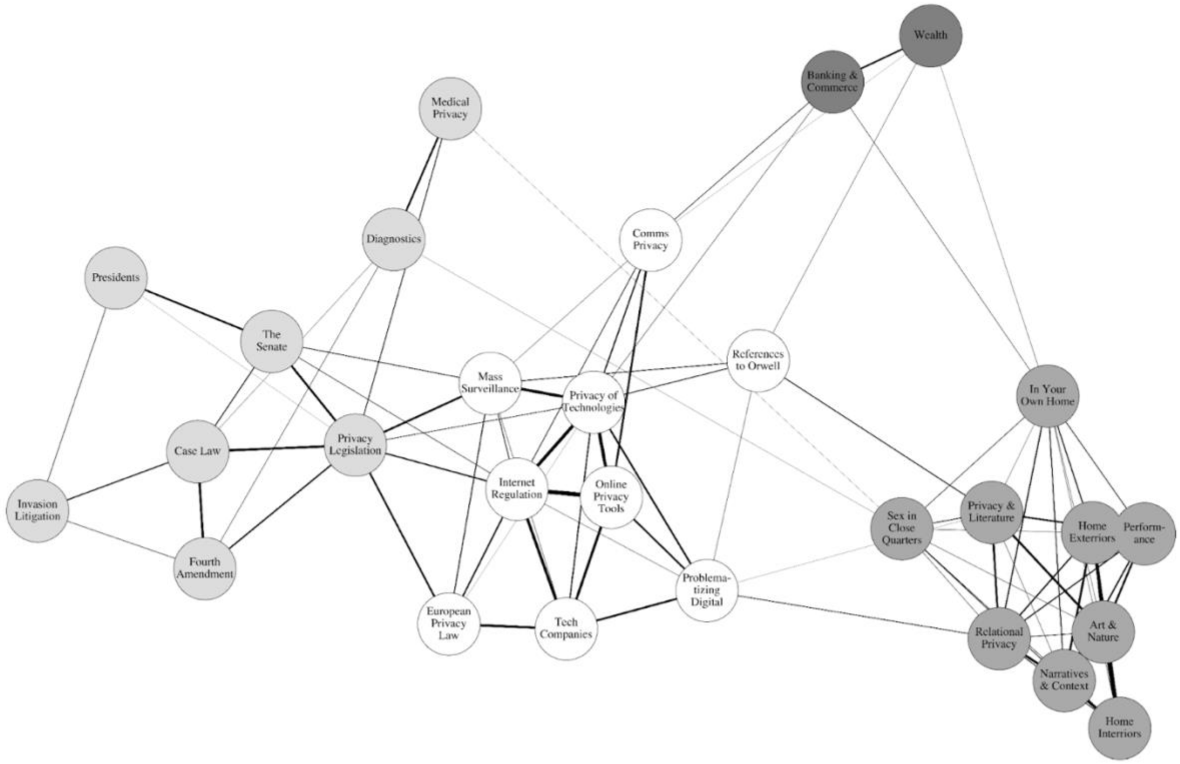
Counter to the idea that privacy is constantly evolving (Viseu et al., 2004; Igo, 2018a), this analysis indicates there is stability in privacy discourse. New topics did emerge, changing the composition of privacy discourse. Established topics, however, did not disappear. The level of sanctity frames across subjects was stable. Rates of transactional language did change, but the decrease was small in legal discourse. In privacy discourse, new topics emerged and used frames at different rates. However, this analysis finds more stability than rapid and constant change in privacy discourse overall.

This analysis has the following limitations. It is based on data from The New York Times. Though this is a single paper, it has a high-quality digital archive that enables this large analysis, and its historical and contemporary influence underscore that this text is meaningful (Golan, 2006; Meraz, 2009). A greater limitation is that news is a form of elite discourse. Because class and citizenship are central to defining privacy issues (Igo, 2018a; Anthony et al., 2017), this analysis may miss the privacy topics important to non-elites, who may have the least privacy. This analysis is based on a keyword search, and so may miss topics related to privacy that are not framed as privacy issues, such as police surveillance (Brayne, 2017) or the 'attention economy' (Franck, 2019). The analysis also focuses on two prominent frames, but other frames may play an important role in shaping messages about privacy, like care (Stark & Levy, 2018) and fairness (Kiviat, 2019; Kiviat, 2021).

This paper's contribution is in comparing different kinds of privacy discourse. This provides empirical support for many privacy theories, and broader context for studies that closely analyze particular contexts of privacy at particular times. More research is needed to understand the mechanisms behind how privacy is framed, and why framing changes over time. Many of the technology topics emerged during the period observed in the corpus, and initially used frames at different rates than established privacy topics. This suggests new privacy topics are affected by external discourses, and future analysis can trace how frames enter privacy discourse, and whether privacy discourse affects frames in other topics as well. Culture shapes the meaning of privacy, and so future research should consider how definitions and frames of privacy vary cross-culturally. Finally, further research should explore the effect of framing privacy as a transaction. Transactional language is much more prevalent in privacy discourse about technology than more established discourses, and so understanding the effect of this frame is key to understanding one of the greatest shifts in the meaning of privacy.

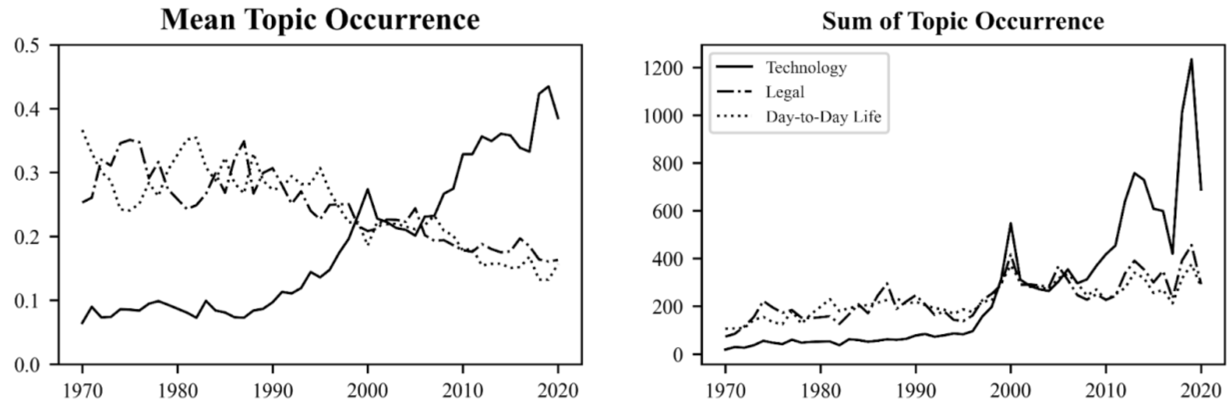
Figures

Figure 2.1. Correlations and Cluster Structure among Privacy Topics.



All nodes with a correlation above 0.01 are connected by an edge. Edges are weighted by correlation strength.

Figure 2.2. Occurrence of Technology, Law & Policy, and Day-to-Day Life Topics by Year.



The panel on the left shows the mean topic score across articles by year. The panel on the right shows the sum of all topic scores by year. The variables for the Technology, Legal, and Day-to-Day Life topics were created by summing the topic scores for the topics in each cluster.

Figure 2.3. Average Prevalence of Transactional and Sanctity Language, 1970–2020.

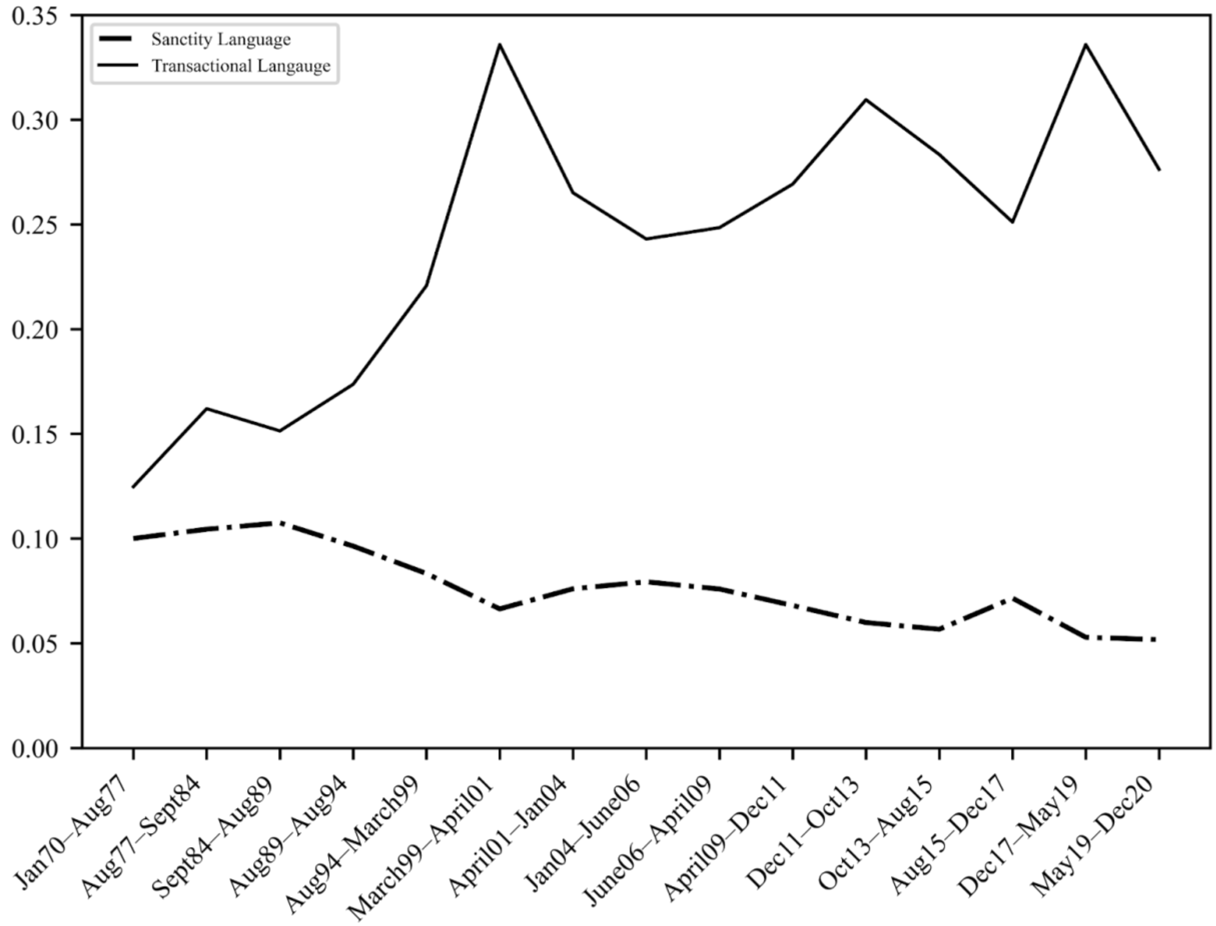


Figure 2.3 shows the proportion of paragraphs containing language related to sanctity or transactionality in evenly sized, chronological bins. Transactional language increased over time ($r(53,368) = 0.123$, $p = 0.000$), and sanctity language decreased ($r(53,368) = -0.061$, $p = 0.000$).

Figure 2.4. Proportion of Paragraphs Containing Transactional and Sanctity Language among Paragraphs Most Characteristic of Each Cluster.

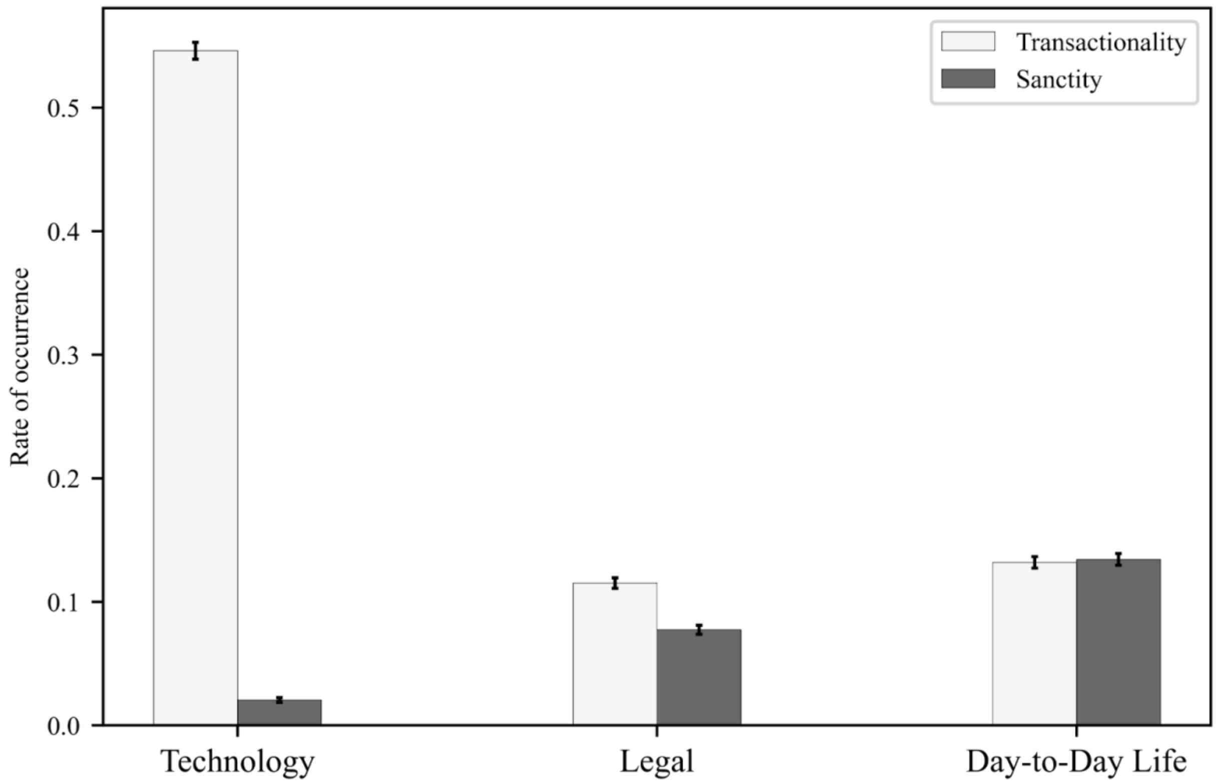


Figure 2.4 shows how often language corresponding to transactionality or sanctity occurs in the 10% of paragraphs most characteristic of each cluster. Error bars represent standard error of the mean.

Figure 2.5. Mean Use of Transactional and Sanctity Language in Paragraphs Most Characteristic of Technology, Law & Policy, and Day-to-Day Life Clusters Over Time.

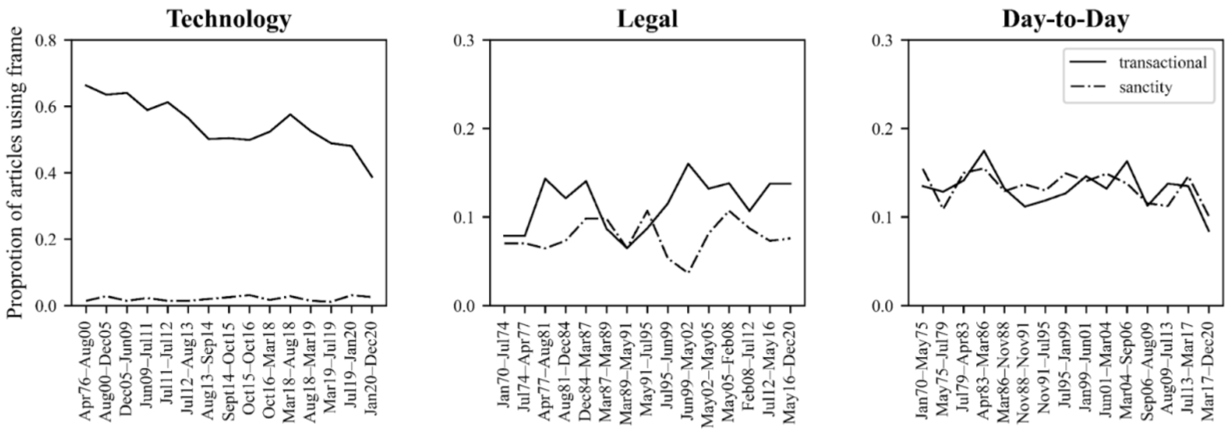


Figure 5 shows the occurrence of transactional and sanctity words among the 10% of paragraphs most characteristic of each cluster of topics over time. Time is represented by evenly sized chronological buckets. Each topic occurs at different rates over time, and so the x-axes for these graphs are different.

Appendix: Tables

Table 2.1A. Overview of Complete Structural Topic Model.

Topic Shorthand	Summary	% of paragraphs best characterized by this topic	FREX Terms	Most Probable Terms
Technology				
Privacy of Technologies	Focus is on technologies and their capabilities (e.g. cameras, sensors, algorithms)	5.01%	facial, devic, databas, card, credit, biometr, store	use, data, inform, technolog, concern, collect, person, track, system, can
Online Privacy Tools	Instructions for people to see and edit their privacy settings on many online platforms	4.32%	click, site, post, blog, polici, default, profil	polici, user, site, inform, web, set, share, post, person, compani
Tech Companies	Reporting focused on major technology companies, especially online platforms.	3.58%	zuckerberg, silicon, apple’, tech, analytica, whatsapp, uber	facebook, compani, googl, data, tech, appl, user, facebook', like, company
Internet Regulation	Discussion of how to regulate internet companies, and if self regulation is sufficient	3.32%	consum, internet, self-regul, microsoft, advertis, trade, industri	compani, internet, consum, onlin, privaci, industri, advertis, commiss, trade, market
Problematizing Digital	Discussion characterizing and problematizing digital privacy	3.29%	’ve, ’re, isn’t, can’t, doesn’t, ’ll, don’t	can, way, don't, peopl, 're, social, digit, time, will, world
Comms Privacy	Privacy in communications (e.g. e-mail, mail)	0.79%	mail, postal, send, flood, e-mail, sent, sign	servic, messag, list, e-mail, receiv, letter, sign, address, send, email
Law, Policy, and Regulation				
Abortion Legal Precedent	Judicial precedents for privacy, largely focused on Griswold v. Connecticut and Roe v. Wade	6.77%	roe, wade, griswold, bork, suprem, abort, sodomi	right, court, constitut, judge, decis, case, state, justic, rule, suprem
Privacy Legislation	Reporting on privacy legislation in the US; combined both legislation under debate and privacy law	5.12%	enforc, act, wiretap, congress, obtain, provis, prohibit	law, protect, govern, act, feder, requir, inform, congress, enforc, bill
Invasion Litigation	Litigation involving charges of invasion of privacy	3.80%	gawker, ravi, defam, libel, bollea, clementi, wrestler	invas, news, charge, case, suit, press, claim, invad, publish, report
Mass Surveillance	Reporting about the National Security Agency and other surveillance initiatives, primarily in the United States	3.44%	snowden, nsa, terrorist, encrypt, contractor, intellig, secur	secur, nation, program, govern, surveil, comput, agenc, intellig, system, american
European Privacy Law	Coverage of European privacy law, especially data protection measures	3.02%	europe’, europ, european, country’, germani, unit, compli	state, unit, rule, regul, european, data, countri, protect, american, law
The Senate	Privacy action in the US Senate	2.30%	democrat, republican, committe, subcommitte, senat, vote, candid	issu, question, senat, rais, democrat, committee, repres, vote, hear, republican
Fourth Amendment	Discussion of the Fourth Amendment (protection from unreasonable search and seizure)	1.52%	polic, reason, expect, fourth, camera, legitim, unreason	reason, expect, search, polic, public, camera, result, intrus, offic, fourth

Presidents	Most often discussions of presidents & other leaders seeking privacy, some comments from presidents on privacy policy	1.10%	nixon, presid, clinton, angel, francisco, vice, bush	presid, hous, white, meet, mrs, clinton, bush, administr, staff, insist
		Social Life		
Relational Privacy	Descriptions of having (or not having), wanting (or not wanting) privacy from other people and groups of people	5.76%	want, dont, your, els, someon, everyon, that	want, peopl, like, get, say, know, just, can, thing, feel
Narratives & Context	First person narratives and descriptions of narrative contexts that invoke privacy	2.67%	stadium, morn, coffe, sat, motel, tire, walk	day, night, back, now, walk, hour, one, two, car, morn
Sex in Close Quarters	Privacy related to sex and sexuality in close living quarters, such as in the military & in temporary settlements	1.35%	inmat, lack, men, male, women, soldier, stress	women, lack, men, prison, forc, live, militari, sexual, sex, often
References to Orwell	References to George Orwell and the language of *Nineteen Eighty-Four*	0.84%	fear, orwellian, brother, computer, erod, ultim, big	big, fear, threat, everi, loss, brother, may, ultim, power, pose
		Art		
Privacy & Literature	Topic is focused on literature; privacy is invoked sometimes in discussing the writing process, sometimes as the topic of writing.	3.36%	book, novel, fiction, diari, literari, biographi, writer	life, book, mean, write, seem, word, one, privat, sens, writer
Art & Nature	Aesthetic writing, especially about landscapes; some excerpts are about art, some are about privacy in nature	2.06%	earphon, paint, color, galleri, painter, sculptur, theatric	tabl, art, like, paint, work, color, one, imag, dark, seem
Performance	Topic is focused on performers and performance (e.g. music, theater); privacy is invoked both in discussing the creative process, and as the subject of art	1.12%	album, movi, "invas, film, singer, actor, debut	play, film, movi, celebr, perform, music, show, star, artist, game
		Journalistic Norms		
Decline to Comment	Journalistic convention of printing officials and spokespeople declining to comment	5.04%	spokesman, rotenberg, marc, spokeswoman, attorney, depart, releas	offici, violat, depart, inform, investig, said, file, releas, general, report
Omitting Names	Reflects journalistic convention of explaining names or identifying information have been changed to protect subjects	2.53%	withheld, child, name, -year-old, children, donor, birth	name, protect, children, parent, ask, child, identifi, mother, -year-old, anonym
Requests for Privacy	Journalistic convention of printing requests for privacy, often by those grieving a loved one	2.44%	respect, father, death, wife, die, famili, griev	famili, respect, friend, time, ask, wife, death, father, husband, guard
Nonprofits	References to and quotes from nonprofits, often the American Civil Liberties Union and the Electronic Frontier Foundation	2.23%	frontier, civil, libertarian, intel, foundat, alarm, smith	group, civil, advoc, liberti, critic, electron, privaci, american, center, organ
Quotes	Reflects journalistic convention of printing a quote and attributing it to a source.	2.17%	"'s, beth, "peopl, said, dixon, giuliani, "'ve	said, peopl, need, execut, director, chief, think, offic, work, beliv
Scholarship	References to ideas of scholars or quotes from scholars	0.93%	analysi, studi, decad, mellon, professor, scholar, andrew	public, studi, univers, research, professor, figur,

				decad, perhap, insitut, journalist
In your own home	Writing that uses the phrase "in the privacy of your own home"	0.55%	lose, vacat, televis, home, percent, winner, survey	home, percent, televis, show, lose, survey, half, found, draw, watch
Commerce & Finance				
Banking & Commerce	Combines discourse about privacy law and banking, as well as privacy for clients who bank offshore	0.93%	gun, bank, money, client, pay, fund, budget	bank, million, pay, cost, money, financi, client, check, price, spend
Wealth	Focus on wealth and assets; sometimes privacy is a characteristic of wealth management, sometimes privacy is a trait of an asset	0.60%	ownership, agent, wire, asset, real, liabil, incom	real, corpor, tax, agent, return, properti, alway, sale, incom, busi
Biomedical Privacy				
Medical Privacy	Privacy related to healthcare and medicine, including laws like HIPAA	2.28%	patient, hipaa, doctor, medic, patients', clinic, health	health, patient, medic, care, record, hospit, insur, costor, confidenti, treatment
Diagnostics	Diagnostic testing including: testing athletes for steroid use, drug testing employees, and HIV antibody testing	1.95%	test, hiv, mandatori, dna, genet, athlet, employ	test, employe, drug, employ, worker, aid, team, player, genet, job
Physical Space				
Home Interiors	Descriptions of home interiors	3.53%	space, window, bedroom, closet, wall, door, floor	room, space, design, door, wall, open, window, bedroom, build, light
Home Exteriors	Descriptions of privacy outside of homes and in neighborhoods	3.13%	neighborhood, neighbor, resid, land, greenwich, citi, gate	hous, citi, street, resid, communiti, live, town, neighbor, new, park
Resources				
Resources for students & teachers 1	Resources for teachers and students that include discussion questions about privacy	1.76%	campus, teacher, students', school, colleg, graduat, student	call, student, school, phone, educ, telephon, number, colleg, articl, board
Tourism guides	Guides for tourism	1.24%	hotel, sea, tenni, beach, restaur, golf, resort	hotel, restaur, room, beach, island, travel, guest, club, pool, air
Resources for students & teachers 2	Academic Content Standards	0.60%	benchmark, understand, civic, econom, conflict, societi, valu	understand, right, individu, import, polit, standard, societi, valu, person, american
Imperfect Topics				
imperfect topic 1	—	1.28%	debat, begun, grow, battl, doubleclick, bloomberg, last	year, last, new, week, move, debat, york, month, increas, chang
imperfect topic 2	—	0.73%	make, sure, disturb, demand, must, mistak, imposs	make, must, even, will, may, sure, need, less, demand, avail
imperfect topic 3	—	0.68%	complic, still, anoth, brook, wari, teeth, penchant	one, still, anoth, yet, even, though, complic, point, remind, might

imperfect topic 4	—	0.52%	doubt, vanish, otherwis, oblig, wish, owe, disappoint	wish, public, will, otherwis, doubt, assur, oblig, per, one, keep
imperfect topic 5	—	0.31%	saudi, eros, barri, online”, task, trend, seen	seen, commerci, toward, fight, conserv, task, exploit, attitud, relig, liber
imperfect topic 6	—	0.00%	mani, part, will, now, other, far, also	will mani, also, new, say, now, one, part, public, even

Appendix: Figures

Figure 2.1A. Distribution of True and Collected Articles Over Time.

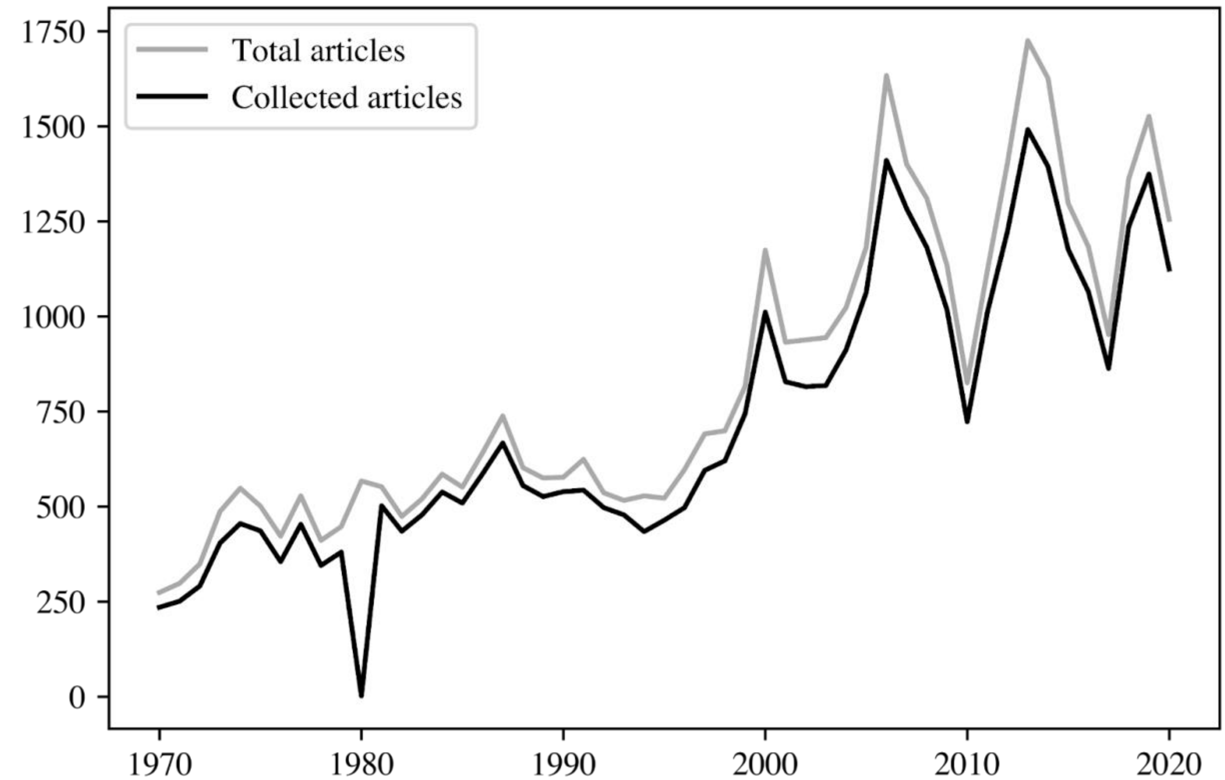


Figure 2.2A. Transactional Language Dictionary.

acquir*	conciliat*	expensiv*	patron*	supplier*
agreement*	consumer*	exploit*	peddle	swap*
arrang*	contract*	haggl*	price*	switch*
asset*	cost	interchange	procur*	trade
bargain*	costlier	market*	purchas*	traded
barter*	costliest	merchant*	purchaser*	trades
broker*	costly	negotiat*	purveyor*	transact*
buy*	customer*	obtain*	retailer*	user*
buyer*	deal*	pact*	shopper*	vendor*
commerc*	exchang*	parley*	substitut*	worth
				worthless

CHAPTER THREE: THE DISPARATE IMPACTS OF RELATIONSHIP-CENTERED MESSAGES ON PRIVACY CONCERNS, PROTECTIVE HEALTH BEHAVIOR, AND VACCINATION AGAINST COVID-19

Introduction

The Covid-19 pandemic has required sweeping social and behavioral changes. These changes are likely to continue while vaccines and treatments are not available globally, and new variants of the virus continue to emerge. Public health agencies have used a variety of messages to encourage beneficial behavior during this prolonged pandemic. Yet the pandemic has also made it clear that people, depending on their social contexts, vary in their judgment of whether to follow public health guidance.

Though public health surveillance has always relied on information collected from members of the public, the capacity of digital technology to support large-scale, real-time data collection meant willingness to share health information took on new importance. The promises of digital public health technologies are many, including personalized information about risk and exposure, and improvements to community outreach and overall care (Ferretti et al., 2020). Both governments and private companies have developed new technology and disease surveillance programs with varying degrees of success (Public Health, Surveillance, and Human Rights Network, 2021). However, a key challenge of these technologies is that their effectiveness depends on what proportion of the public participates, structure of disease spread, as well as material and social context (Ferretti et al., 2020; Cebrian 2021; Farrahi, Emonet, & Cebrian, 2014). These technologies also pose varying risks to privacy, which may not always be known to the public (Public Health, Surveillance, and Human Rights Network, 2021).

Given the varying benefits and risks of sharing health information, people vary in their decisions to share their information in the service of public health. Understanding how people make choices about their information, then, is an important component in the success of participatory surveillance programs. Initial surveys find there is relatively low public support of surveillance policies meant to decrease the spread of Covid-19, and suggest this is a barrier to their widespread adoption (Zhang et al., 2020). Relatively little is still known about how much people vary in their willingness to share information with public health officials, and why.

Likelihood to practice protective health behavior and get vaccinated are better-studied. Both are associated with a variety of demographic factors, attitudinal factors, social and cultural factors, as well as differences in access and knowledge (Taylor, 2018; Dubé, 2013). Yet studies of how to most effectively promote protective behavior and vaccination are ongoing. Studies of the role of altruism, for example, in the Covid-19 pandemic are mixed (Sheth & Wright, 2020; Pfattheicher et al., 2020; Campos-Mercade et al., 2021), as is previous research on altruism promoting messages about vaccinations and other diseases (Hendrix et al., 2014; Betsch, Böhm, & Korn, 2013; Shim et al., 2012). Though protective behavior and vaccination are the subject of a great deal of research, encouraging behavioral change and vaccination remain difficult problems.

One possible reason prior findings are mixed could be related to reference groups. Often, altruistic messages focus on how actions benefit society rather than highlighting benefits to people participants are connected to in their real lives. Studies have shown that social proximity to beneficiaries increases levels of altruism and reciprocity (Simpson & Willer, 2015). Moreover, social proximity alters perceptions of probabilities: people perceive events that happen in their social circle to be more likely to happen generally (Tversky & Kahneman, 1973; Keller, Siegrist, & Gutscher, 2006). Encouraging people to think about their immediate social networks may alter assessments of risk and increase the likelihood of respondents supporting public health measures.

This theory is bolstered a growing recognition that tapping into one's cognitive understanding of their personal network ("network cognition") can produce different behavior (Bishop Smith et al., 2020). However, this phenomenon has yet to be broadly applied to public health. Privacy behavior is highly context dependent, and so it may be especially responsive to subtle framing effects compared to the "actual" behavioral changes often studied in health communication (e.g. condom use, vaccinations) (Acquisti, Brandimarte, & Loewenstein, 2015).

Present Study

The primary purpose of this study is to understand how data sharing behavior compares to more established behaviors like protective health behavior and vaccination. I investigate these differences using relationship-centered communication experiments and correlational analysis of the data. Relationship-centered messages ask respondents to consider the experiences of people they know as part of their messaging. This type of message applies network cognition theories that expect the perceptions people hold of their own social ties to affect their judgments of probabilities. In my experiments, I test whether these relationship-centered messages increase respondent support for public health. I tested the effect of three different relationship-centered messages: one message about protecting high-risk loved ones, one message about how a virus might spread through a respondent's social network, and one message about the financial hardship loved ones may experience because of the pandemic.

I chose messages for the experimental conditions that appeared in communication about the pandemic during the periods I ran the experiment. This enabled us to explore the effect of salient messages as the social context of the pandemic changed. Altruistic and prosocial messages are common in prior research and have been applied to public health communication throughout this pandemic. The message about protecting high-risk loved ones applies a version of this altruistic message. Prior research shows social network interaction affects risk perception (Kohler, Behrman, & Watkins, 2007). Communication about Covid-19 often implicitly discusses interpersonal disease spread, but less often explicitly evokes the role of social network structure. The disease spread message explicitly connects disease spread with each respondent's personal network. Finally, prior research finds perceptions of Covid-19 shaped economic anxiety (Fetzer et al., 2021). Given the amount of attention paid to the economic impacts of the pandemic, I use the financial hardship condition to consider if economic anxiety also shapes Covid-19 behavior. I expected each message to increase respondents' likelihood to practice protective behavior and their willingness to share data. I find a significant effect of the message about protecting high-risked loved ones on privacy behavior. I find no other significant effects of the experimental conditions on the outcome variables.

The second purpose is to analyze the socio-demographic factors associated with willingness to share data. I compare these relationships to those correlated with likelihood to practice protective behavior and get vaccinated. I find privacy behavior is differently associated with demographic and attitudinal factors compared to protective behavior and vaccination. Consistent with (Zhang et al., 2020), this study suggests willingness to share data is a distinct public health behavior. This work underscores that people do not necessarily adopt all public health behaviors to the same extent.

Methods

I test whether three relationship-centered messages increase public health outcomes: an altruistic message about protecting high-risk loved ones ("prosocial message"), a message about disease spread through one's network ("disease spread message"), and a message about the economic effects of the pandemic ("hardship message"). In my pre-registered hypotheses (see

Supplementary Materials 3.1A), I expected each of the messages to increase support for information sharing and likelihood to engage in protective behavior compared to the controls.

I conducted a series of online survey experiments. For each experiment, respondents were randomly assigned to the experimental or control condition. Please see Figures 2.1A–2.3A in supplementary materials for wording of each control and experimental condition. Within each experimental condition, respondents read a short text passage and answered a series of write-in questions. Within each control condition, respondents read a short informational passage about Covid-19 from the Centers for Disease Control. The passage includes information about Covid-19 symptoms, how to prevent the spread of the virus, and what to do if someone becomes sick. Respondents in the control condition then answered a series of write-in questions about contagious diseases.

Respondents were recruited through the research firm Qualtrics. All respondents were US residents over the age of 18, and the sample adhered to quotas for gender (50% male, 50% female), race (~66% non-Hispanic white, ~12% black, ~12% Hispanic, ~10% other), and education (50% some college or less, 50% associates and above). I use this quota sampling approach to collect a sample that corresponds to the sociodemographic characteristics of the US population. Attention and consistency checks ensured respondents read the material and gave consistent answers. Qualtrics panelists are subject to identity verification to prevent duplicate respondents. This research was approved by the Institutional Review Board (IRB) of the University of California, Los Angeles. The IRB granted a waiver of informed consent for this research.

Experimental Conditions

Prosocial Message: Protecting High-Risk Loved Ones

This condition encouraged respondents to think about protecting loved ones at high risk for serious illness from COVID-19. Respondents read an excerpt from the CDC's website explaining COVID-19 with information about preventive health behavior. It also featured the phrase "Protect yourself, protect others" in bold. Respondents were then asked to think of two to five people at risk for serious illness from COVID-19, and list their relationship to them in a free response box. Respondents were then asked to think of two to five people who their friends or family would want to protect from COVID-19, and list them as well. Data for this condition and control were collected between April 3 to April 8, 2020. A total of 50 respondents were randomly assigned to the control, and 47 respondents were randomly assigned to the prosocial message. This condition considers whether an altruistic, network-based message increases preventive health behavior compared to a similar message without a network-based, altruistic prime.

Disease Spread Message: Imagining Disease Spread Through One's Personal Network

This condition asked respondents to imagine the spread of COVID-19 through their personal network. Respondents read an excerpt from a New York Times op-ed that described exposure to COVID-19 through a family member, and traced potential spread through the author's personal network. Respondents were then asked to imagine disease spread through their own network by listing 2-5 pairs of people in written response boxes, with the first listed person being someone the respondent could contract COVID-19 from, and the second being someone the first listed person could contract COVID-19 from.

Respondents were not explicitly asked to imagine the disease spreading among their loved ones, though the examples given in the question suggested naming socially close people. Most respondents named some people they are socially close to (e.g. friend, mother), and some chose people they are socially further from (e.g. Uber driver, cashier). I coded responses per their social closeness. Responses were considered "socially close" if they were one of the following: (1) a family relation, (2) a friend, or (3) were identified by name. Respondents who named at least one socially close person were considered suggestible to the prime. After responses were coded, 134 out of 148 responses met this criterion.

Data for this condition were collected in two waves: October 19 - 28, 2020, and November 20 - 25, 2020. A total of 102 respondents were randomly assigned to the control, and 148 respondents were randomly assigned to the disease spread message. This condition tests whether thinking about disease spread in terms of one's network increases preventive health behavior compared to general information about disease.

Hardship Message: Considering Economic Hardship Caused by the Pandemic

This condition encouraged respondents to think of people in their personal network who experienced financial hardship after the onset of the pandemic. In this condition, respondents read a news excerpt from the New York Times about unemployment claims in the United States. They were also asked to list their relationship to 2-5 people experiencing financial hardship whom they would like to help, and to briefly describe how that person had been affected by the pandemic in written response boxes. Data for this condition was collected from May 1 to May 11, 2020. A total of 73 respondents were randomly assigned to the control, and 69 respondents were randomly assigned to the hardship message. This condition tests whether thinking about secondary effects of addressing the pandemic in terms of one's network increases preventive health behavior.

A limitation of these experiments is that I do not include control conditions of the same topic as the experimental conditions, but with general messages rather than relationship-centered messages. Instead, I compare the experiments to similar control conditions. I am thus unable to test whether using a relationship-centered message produces a stronger effect than discussing a topic generally. However, an advantage of this design is that conditions are more comparable to one another.

Outcome Measures

Data Sharing

Respondents across surveys were asked how strongly they agreed or disagreed with their own data being collected for surveillance on a 5-point Likert scale. The questions addressed accessing phone location data, publicizing the identity and location of those diagnosed with COVID-19, and using tracking devices to enforce quarantine. There were five questions in total. These questions were drawn from policies discussed in or adopted by China, South Korea, Singapore, and the United States by the end of March 2020. Many of these measures would violate privacy norms in the US, where this data collection took place. However, surveying respondents on norm-violating policies allows us to measure the extent to which emergency circumstances change norms. Respondents' answers to the five questions were averaged to create the data sharing variable. Low scores indicate a high support of privacy at the expense of surveillance, and high scores indicate high willingness to share information at the expense of privacy. Scores of this variable range from 1–5.

Protective Behavior

This variable measures how likely respondents were to practice protective behavior on a 5-point Likert scale. In the disease spread and hardship message experiments, respondents were asked three questions: if they were likely to wear a face mask, step away if someone stood near them, and avoid crowded places in their everyday lives. In the prosocial message experiment, respondents were asked to imagine they exhibited symptoms of COVID-19, and then rated their likelihood to do three things: wear a face mask, self-isolate, and encourage others to “stop the spread.” The health behavior variable is the mean of each respondent’s answers. Scores of this variable range from 1–5.

Vaccination Intent

Respondents surveyed between October and November 2020 were asked how strongly on a 5-point Likert scale they agreed with the statement: “I plan to get vaccinated for COVID-19 when a vaccine is approved by the FDA.” The response to this singular question measures intent to be vaccinated. Pfizer released clinical data and filed for emergency authorization for its Covid-19 vaccine on November 20, 2020, the first day of the November wave of data collection. This likely caused different attitudes toward vaccination between these two waves.

Independent Variables

Party Identification (ID)

I used the partyid question of the General Social Survey. A binary variable was created by grouping respondents who identified as Democrats or as Democrat-leaning, and excluding those who identified as wholly independent or other.

Race

The race variables are self-identified and not mutually exclusive.

Education

Respondents are grouped by their highest level of education: a high school diploma, an associate’s degree or some college, a bachelor's degree, or a graduate degree.

Racism and Xenophobia

Respondents surveyed between October and November 2020 answered four questions of the explicit racial resentment scale (Wilson & Davis, 2011) and seven questions to measure xenophobia (Chapman Survey of American Fears, 2014). Responses to each scale were highly positively correlated ($r(411) = 0.659$, $p = 0.000$). I averaged responses to make a single variable.

In the correlational analysis, I analyze the interaction between political ID and time, education, racism and xenophobia, gender, and age. Political ID was consistently predictive of behavior during this period of the pandemic (Allcott et al., 2020; Makridis & Rothwell, 2020), and so it is a major focus of this analysis. I chose the other variables for the following reasons: the circumstances of the pandemic changed from month to month, and so I examined the association between the outcome variables and time. I included education, gender, and age because they are demographic factors that are often predictive of health behavior. Some people responded to the pandemic with racial animosity (Reny & Barreto, 2020; Jutzi et al., 2020), and so I also analyze the association with racism and xenophobia. Compositional differences and sample size preclude us from making comparisons about the interaction of race and party ID. The associations between race and the outcome variables are available in Table 3.3A.

Results

First, I analyze the effect of the experimental conditions on data sharing and protective behavior. I expected each of the personalized messages to increase respondents' likelihood to share data and practice protective behavior. Respondents shown the prosocial message were significantly more likely to share data ($M = 3.183$, $SD = 0.850$) at the expense of privacy than respondents assigned to the control, $t(95) = 2.809$, $p = 0.006$, a difference of 0.535 points on average. I did not find evidence that the disease spread message significantly increased data sharing among all surveyed respondents ($M = 2.797$, $SD = 1.033$), $t(248) = 1.595$, $p = 0.112$.

However, among respondents who imagined contracting Covid-19 from at least one socially-close contact, there was a marginal positive effect (*M* = 2.831, *SD* = 1.0144), *t*(234) = 1.829, *p* = 0.067. This provides weak evidence of an effect among those who were impressionable to the priming condition.

I do not find evidence the hardship message affected support for data sharing (*M* = 2.913, *SD* = 1.079), *t*(140) = -1.171, *p* = 0.243, nor evidence any of the messages affected likelihood to practice protective behavior: prosocial message: (*M* = 4.362, *SD* = 0.881), *t*(95) = -0.394, *p* = 0.694, disease spread message: (*M* = 4.086, *SD* = 0.945), *t*(248) = 0.232, *p* = 0.817, hardship message: (*M* = 4.193, *SD* = 0.952), *t*(68) = 0.774, *p* = 0.440. Respondents were asked about vaccination intent only in the disease spread message experiment, and there was no evidence of an effect of that message (*M* = 3.581, *SD* = 1.405), t(248) = 0.701, *p* = 0.484. See Table 3.2A for a full overview of all condition means and standard deviations.

There are multiple reasons why the messages in the experiments affected data sharing but not protective behavior. A likely explanation is that protective health behavior was a much more salient topic during this period than data sharing, and so respondents may have had stronger priors. It is possible data sharing is more responsive to framing effects than protective behavior in general. Data sharing may be more susceptible to subtle messaging in part because it is less-often the subject of directive messaging. It is also possible that different types of messages motivate different kinds of behavior.

I perform a secondary analysis to consider the extent to which data sharing, protective behavior, and vaccination are predicted by similar traits. These variables are only weakly correlated with each other (Table 3.1A). They are associated with different demographic traits, particularly political ID (Table 3.3A). To better understand how political ID and other factors relate to each other, I explore interactions in the association between political ID and time, education, gender, age, and racism and xenophobia and the outcome variables in Figure 3.2. Since the respondents were randomly assigned to their experimental conditions and thus confounding by experimental conditions is unlikely, I pooled the subjects from all conditions to yield more stable estimates. Yet the results reported here should be still understood as general trends rather than as precise point estimates. See Table 3.4A for a full set of regression results.

One's likelihood to practice each behavior is significantly associated with political ID. While this could suggest simple polarization, my analysis suggests the relationship between political ID and public health behavior is sometimes moderated by other factors. The factors that moderate political ID vary across the three outcome variables. This means the relationship between party ID and behavior varies both by respondent and by type of health behavior. Specifically, both political ID and socio-demographic traits are related to data sharing: Democrats reported higher likelihood to share data than Republicans overall, but the likelihood also varies by gender, with men from either party more likely to share data than women. The likelihood to share data declined with age among Republicans but not Democrats. Likelihood to share data is also polarized among respondents with some college or a bachelor's degree, but not among respondents with a high school diploma or a graduate degree (top panel).

In comparison, Democrats reported a significantly higher likelihood to practice preventive health behavior than Republicans regardless of gender and age (middle panel). With the exception that Republicans with a graduate degree have similar levels of health behavior compared to their Democrat counterparts, there is no evidence education moderates the association between party ID and health behavior.

The interaction of racism and xenophobia with political ID was consistent for data sharing and protective behavior. Figure 3.2 shows that both data sharing and health behavior were more strongly associated with racism and xenophobia among Republican respondents than among Democrat respondents.

There is no evidence political ID moderates the relationship between either age or education with these dependent variables. Older respondents were marginally more likely to intend to get vaccinated than younger respondents, and respondents with higher levels of education are significantly more likely to get vaccinated than those with lower levels of education. In this sample, female Republicans were significantly less likely to intend to be vaccinated than male Republicans, female Democrats, or male Democrats. One possible explanation for this difference is explored in Figure 3.1A.

Discussion

Despite the possibilities of digital technology for public health surveillance, initial measures of public support for these technologies was low (Zhang et al., 2020). Little is known about the mechanisms that cause people to support data sharing for public health. The purpose of this analysis is to contribute to understandings of the factors that affect how willing people are to share their personal information to support public health. I first analyze the effect of three relationship-centered messages to explore how personalized framing of the pandemic affects willingness to share data. I then conduct a correlational analysis to understand the relationship between political ID, socio-demographic characteristics, and three different kinds of public health behavior.

In these experiments, I found the message about health risks to respondent’s loved ones increased respondent support for data sharing, but the messages about economic hardship did not. I found weak evidence that messages about risk of disease spread in one's community may increase willingness to share data among some people. Compared to data sharing, other protective health behaviors like wearing a mask were not affected by such relationship-centered messages. It is difficult to change opinions about a salient topic, and so this may explain why our priming materials changed responses to privacy questions but no other health behaviors. These results suggest that how public health messages are framed can affect how willing people are to share their information. However, the experiments are inconclusive about the distinct effects of context and message content, and the effects I find are small. While this work asks novel questions, I suggest replication and expansion of this work is needed to understand what makes people willing to share their personal information and measure the effectiveness of messaging campaigns for behavioral change.

The protective health behaviors I studied have different patterns of association with socio-demographic variables and attitudes. Specifically, consistent with prior research about the role of partisanship in the Covid-19 pandemic, I find protective behavior is primarily associated with political party ID (Makridis & Rothwell, 2020). Intent to be vaccinated was correlated with age, level of education, and an interaction between gender and political party ID. This is also consistent with earlier trends in vaccination during the Covid-19 pandemic (Khubchandani et al., 2021) and prior to it (Bish et al., 2011). Finally, I found the association between political party ID and data sharing was dependent on several different socio-demographic characteristics, including: age, education, and gender.

Attitudes toward privacy in public health contexts are understudied, and many of the findings are inconsistent (Clayton et al., 2018). This study is consistent with the finding that Democrats tend to be more supportive of secondary use of data than Republicans (Auxier et al., 2019). It is also consistent with a study of privacy in the Covid-19 pandemic that found men, people with higher levels of education, and Democrats were more supportive of a variety of types of surveillance (Zhang et al., 2020). This analysis adds that the interaction between socio-demographic characteristics and political ID is important in the prediction of data sharing. This observation is not obvious given that protective health behavior is more straightforwardly polarized.

This study contributes two additional findings. First, the correlational analysis finds racism and xenophobia are correlated with protective health behavior and data sharing after controlling for political ID. This suggests resentment against outgroups could decrease practicing important public health behavior. This provides additional support for prior findings about the role of xenophobia, racism, and nationalism in responses to the Covid-19 pandemic (Reny & Barreto, 2020; Jutzi et al., 2020).

Second, the experiments explored whether relationship-centered messages can affect respondent behavior. There is a growing recognition that tapping into a person's cognitive understanding of their personal network can produce different behavior (Bishop Smith et al., 2020). This phenomenon has yet to be broadly applied to public health, even though it may be especially relevant because it can shape perceived risks and benefits of interventions (Wang et al., 2015; Meszaros et al., 1996). In this analysis, I am unable to analyze whether relationship-centered messages provoke stronger responses than more general messages on the same topic. However, I hope this preliminary analysis inspires additional research on the role of network-cognition in public health communication.

Limitations

This study has the following limitations. First, it uses only one message type and one control condition per experiment. The messages and the control vary in content, and so I cannot rule out the possibility that the experimental results are the consequence of features of these conditions as opposed to the result of the general messages I tested. Second, each wave of the survey tested the effect of only one experimental condition and one priming condition. The data was collected in four waves over eight months during a time of rapid societal change, and so this design limits the comparability of the experimental results and introduces time as a confounding variable — although the timeliness of the data collection provides information from critical points during the pandemic. Replicating this study by running all three experiments at the same time with additional conditions would clarify the different effects of context, message content, and level of personalization. However, given the increased availability of vaccines and diagnostic tests in the U.S., we may expect less support for data sharing overall.

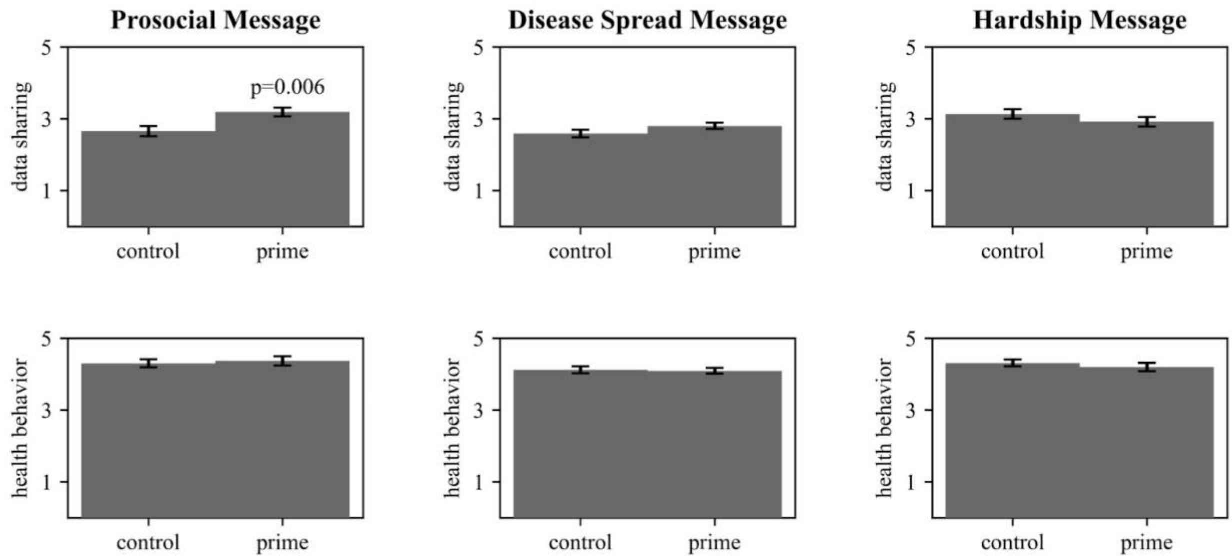
An additional limitation is the potential of self-selection into experimental conditions. The experimental design limits the potential for self-selection by randomly assigning participants to conditions. It is possible, albeit unlikely, that respondents differentially opted-out of conditions. This would limit my ability to make causal claims from these experiments. However, the findings on socio-demographic correlates of behavior are compatible with surveys of larger samples, indicating consistency between these findings and broader behavioral trends.

Implications

This work provides some initial considerations for public health communications strategies to promote data sharing. Traditional altruistic public health messages to encourage data sharing may become more effective if they can incorporate relationship-centered messages. In addition, I found demographic variables were differently associated with data sharing, protective health behavior, and vaccination. My findings suggest groups that require the most intervention to adopt some public health behaviors (e.g. vaccination) may also be different from those who are most willing to share data with public health authorities. The findings of this study support that such selectivity into databases that rely on voluntary data sharing must be considered when authorities try to generalize findings from such databases to members of groups most resistant to behavioral change.

Figures

Figure 3.1. Effect of Relationship-Centered Messages on Data Sharing and Health Behavior.



Bars show mean response for data sharing (first row) and protective behavior (second row) among respondents assigned to the prosocial message (column 1), disease spread message (column 2), or hardship message (column 3). Error shows standard error of the mean. P-value measured by two-tailed t-test.

Figure 3.2. Association Between Independent Variables and Data Sharing, Health Behavior, and Vaccination by Party ID.

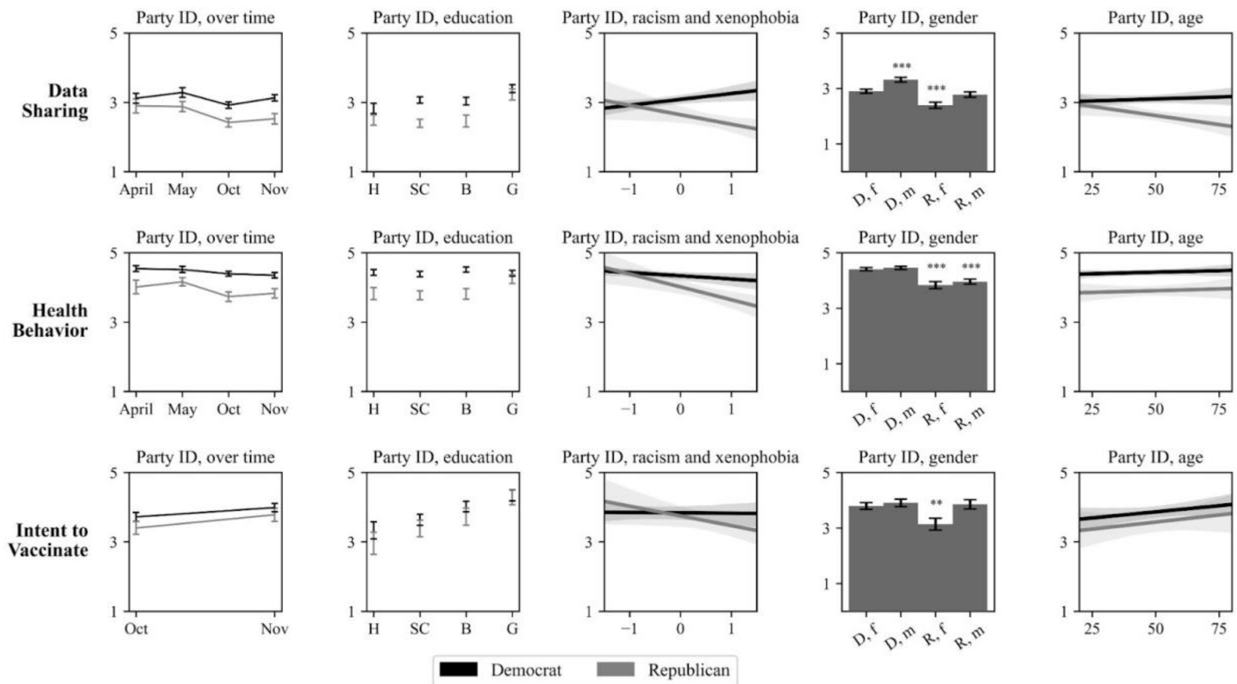


Figure shows relationship between month (column 1), education (column 2), racism and xenophobia (column 3), gender (column 4), and age (column 5) on the x axes and data sharing (first row), protective behavior (second row), and intent to vaccinate (third row) on the y axes. Estimates for Democrats (black) and Republicans (gray). Error shows standard error of the mean, shaded area around the line of best fit represents the 95% confidence interval. The time scales in the first column correspond to the months I collected responses, and are not evenly distributed. The specific dates are: 4/3–4/8, 5/1–5/11, 10/19–10/28, 11/20–11/25. All data collected in 2020. Codes for the x-axis are as follows: H = high school diploma, SC = some college or associate's degree, B = bachelor’s degree, G = graduate degree. D, f = Democrat and female, D, m = Democrat and male, R, f = Republican and female, R, m = Republican and male. *ⱡ = $p < 0.10$, * = $p < 0.05$, ** = $p < 0.01$, *** = $p < 0.001$.* P-value measured by two-tailed t-test.

Appendix: Tables

Table 3.1A. Correlations Among Dependent Variables.

	Data Sharing	Protective Behavior	Intent to be Vaccinated
Data Sharing			
Health Behavior	*r*(650) = 0.327, *p* = 0.000		
Intent to be Vaccinated	*r*(411) = 0.327, *p* = 0.000	*r*(411) = 0.302, *p* = 0.000	

Table 3.2A. Mean and Standard Deviation of Outcome Variables Across Conditions.

	Data Sharing		Protective Behavior		Intent to Vaccinate	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**
Prosocial Control	2.648	1.012	4.295	0.785	-	-
Prosocial Prime	3.183	0.850	4.362	0.881	-	-
Hardship Control	3.129	1.114	4.306	0.779	-	-
Hardship Prime	2.913	1.079	4.193	0.952	-	-
Network Control 1	2.496	1.013	3.845	1.162	3.393	1.358
Network Prime 1	2.797	1.036	4.118	0.923	3.566	1.389
Network Control 2	2.691	1.083	4.442	0.617	4.087	1.262
Network Prime 2	2.797	1.036	4.051	0.972	3.597	1.431

Table 3.3A. Distribution of Demographic and Attitudinal Variables Across Dependent Variables.

	Data Sharing			Protective Behavior			Intent to Vaccinate		
Variable	**n**	**% (95% CI)**	***P***	**n**	**% (95% CI)**	***P***	**n**	**% (95% CI)**	***P***
Age	650	-0.0026, (-0.007, 0.002)	0.262	650	-0.0007, (-0.005, 0.003)	0.737	411	0.0076, (0.000, 0.016)	0.06
Gender									
Male (ref)	327	2.984, (1.899, 4.070)		327	4.150, (3.214, 5.086)		206	3.806, (2.437, 5.175)	
Female	323	2.663, (1.700, 3.626)	0.000	323	4.218, (3.336, 5.100)	0.347	205	3.434, (2.030, 4.838)	0.007
Race									
White (ref)	488	2.784, (1.718, 3.850)		488	4.152, (3.212, 5.092)		316	3.626, (2.187, 5.065)	
Black	88	2.950, (1.984, 3.916)	0.173	88	4.306, (3.488, 5.125)	0.151	49	3.204, (1.761, 4.647)	0.057
Asian	62	3.116, (2.307, 3.925)	0.018	62	4.308, (3.542, 5.074)	0.212	36	3.917, (2.921, 4.913)	0.240
Other	29	2.448, (1.526, 3.370)	0.098	29	3.796, (2.646, 4.944)	0.051	24	3.500, (2.149, 4.851)	0.677
Education									
High School (ref)	129	2.634, (1.630, 3.638)		129	4.109, (3.176, 5.042)		79	3.063, (1.575, 4.551)	
Some College	233	2.713, (1.704, 3.722)	0.474	233	4.098, (3.121, 5.075)	0.916	150	3.453, (2.013, 4.893)	0.055
Bachelor's Degree	154	2.777, (1.743, 3.811)	0.243	154	4.261, (3.393, 5.129)	0.157	104	3.808, (2.546, 5.07)	0.000
Graduate School	127	3.268, (2.258, 4.276)	0.000	127	4.303, (3.477, 5.102)	0.074	74	4.243, (3.135, 5.351)	0.000
Party ID									
Democrat (ref)	307	3.085, (2.104, 4.066)		307	4.429, (3.736, 5.122)		197	3.843, (2.589, 5.097)	
Republican	201	2.624, (1.549, 3.699)	0.000	201	3.905, (2.880, 4.930)	0.000	125	3.568, (2.069, 5.067)	0.077

Other/Independent	142	2.546, (1.570, 3.522)	0.000	142	4.048, (3.041, 5.055)	0.000	89	3.202, (1.739, 4.665)	0.000
Racism and Xenophobia	411	-0.1480, (-0.246, -0.050)	0.003	411	-0.2769, (-0.364, -0.190)	0.000	411	-0.1535, (-0.288, -0.019)	0.026

Table 3.4A. Interactions Between Key Demographic Traits and Party ID on Dependent Variables.

		Data Sharing		Health Behavior		Intent to Vaccinate	
	Variable	**% (95% CI)**	***P***	**% (95% CI)**	***P***	**% (95% CI)**	***P***
Model 1	Time	-0.0348, (-0.145, 0.075)	0.535	-0.0704, (-0.161, 0.020)	0.127	0.2693, (-0.110, 0.649)	0.164
	Republican	-0.0950, (-0.634, 0.444)	0.729	-0.3845, (-0.829, 0.060)	0.090	-0.6573, (-2.784, 1.469)	0.543
	Republican * Time	-0.1312, (-0.314, 0.051)	0.158	-0.0498, (-0.200, 0.101)	0.515	0.1126, (-0.498, 0.723)	0.717
	Intercept	3.1813, (2.855, 3.508)	0.000	4.6246, (4.356, 4.893)	0.000	2.9118, (1.586, 4.238)	0.000
Model 2	Education	0.1610, (0.050, 0.272)	0.005	0.0098, (-0.083, 0.103)	0.836	0.3436, (0.160, 0.527)	0.000
	Republican	-0.6673, (-1.134, -0.200)	0.005	-0.8515, (-1.243, -0.460)	0.000	-0.4591, (-1.242, 0.324)	0.249
	Education * Republican	0.0833, (-0.089, 0.256)	0.342	0.1293, (-0.015, 0.274)	0.079	0.0865, (-0.206, 0.379)	0.561
	Intercept	2.6818, (2.378, 2.986)	0.000	4.4067, (4.152, 4.661)	0.000	2.9708, (2.474, 3.467)	0.000
Model 3	Racism & Xenophobia	0.1688, (0.021, 0.317)	0.026	-0.0928, (-0.224, 0.038)	0.165	3.8376, (3.629, 4.046)	0.908
	Republican	-0.4429, (-0.709, -0.177)	0.001	-0.3202, (-0.556, -0.085)	0.008	-0.0122, (-0.218, 0.194)	0.636
	Republican*Racism & Xenophobia	-0.4425, (-0.703, -0.182)	0.001	-0.2783, (-0.509, -0.047)	0.018	-0.0892, (-0.459, 0.281)	0.147
	Intercept	3.0848, (2.935, 3.234)	0.000	4.3351, (4.203, 4.468)	0.000	-0.2679, (-0.631, 0.095)	0.000
	Female	-0.4139, (-0.640, -0.188)	0.000	-0.0482, (-0.238, 0.141)	0.617	-0.1142, (-0.493, 0.265)	0.553
	Republican	-0.5401, (-0.785, -0.295)	0.000	-0.5041, (-0.710, -0.298)	0.000	-0.0536, (-0.470, 0.363)	0.800
	Female*Republican	0.0325, (-0.331, 0.396)	0.860	-0.0699, (-0.375, 0.235)	0.652	-0.5991, (-1.212, 0.013)	0.055
	Intercept	3.3139, (3.146, 3.482)	0.000	4.4556, (4.314, 4.597)	0.000	3.9070, (3.623, 4.191)	0.000

Appendix: Figures

Figure 3.1A. Conditions for Prosocial Message Experiment.

CONDITION 1

Start of Block: Condition 1

Q4 Can you think of other contagious diseases that, like coronavirus, are contagious and spread from person to person?

Name up to 5 other contagious diseases that spread from person to person.

____

Q55 Can you think of symptoms of coronavirus?

Name up to 5 symptoms of coronavirus you can remember.

____

Page Break

Q5 **Please review the following information about coronavirus, excerpted from the CDC.**

COVID-19 is a new disease, caused by a novel (or new) coronavirus that has not previously been seen in humans.

Current symptoms reported for patients with COVID-19 have included mild to severe respiratory illness with fever, cough, and difficulty breathing.

The best way to prevent illness is to avoid being exposed to this virus. The virus is thought to spread mainly from person-to-person.

Protect yourself, protect others

Stay home if you are sick, except to get medical care.

Cover your mouth and nose with a tissue when you cough or sneeze or use the inside of your elbow.

Wash your hands often with soap and water for at least 20 seconds especially after you have been in a public place, or after blowing your nose, coughing, or sneezing.

Put distance between yourself and other people if COVID-19 is spreading in your community.

If you are sick: You should wear a face mask when you are around other people and before you enter a healthcare provider's office.

Q6 According to the information above, which of the following IS NOT true?

- COVID-19 has not previously been seen in humans (1)
- The best way to prevent illness is to avoid being exposed to COVID-19 (2)
- You should wear a face mask around others if you are sick (3)
- If you use hand sanitizer, it should be 95% alcohol (4)

End of Block: Condition 1

CONDITION 2

Start of Block: Condition 2

Q7 Some people are at high risk for serious illness from coronavirus, including **older adults** and people with **chronic conditions** like **diabetes** and **heart disease**.

Can you think of anyone you'd want to protect from coronavirus?

Please list your relationship to up to 5 people you'd want to protect (ex. "dad," "friend," or "wife")

____

Q8 Can you think of anyone your friends or family would want to protect from coronavirus?

Please list your relationship to up to 5 people your friends or family would want to protect (ex. "friend's grandfather," "mom's coworker")

____

Page Break

Q9 **Please review the following information about coronavirus, excerpted from the CDC.**

Remember that people you care about may be at higher risk for serious illness from coronavirus, including older adults and people with chronic conditions like diabetes and heart disease.

COVID-19 is a new disease, caused by a novel (or new) coronavirus that has not previously been seen in humans.

Current symptoms reported for patients with COVID-19 have included mild to severe respiratory illness with fever, cough, and difficulty breathing.

The best way to prevent illness is to avoid being exposed to this virus. The virus is thought to spread mainly from person-to-person.

Protect yourself, protect others

Stay home if you are sick, except to get medical care.

Cover your mouth and nose with a tissue when you cough or sneeze or use the inside of your elbow.

Wash your hands often with soap and water for at least 20 seconds especially after you have been in a public place, or after blowing your nose, coughing, or sneezing.

Put distance between yourself and other people if COVID-19 is spreading in your community.

If you are sick: You should wear a face mask when you are around other people and before you enter a healthcare provider's office.

Q10 According to the information above, which of the following IS NOT true?

- ○ COVID-19 has not previously been seen in humans (1)
- ○ The best way to prevent illness is to avoid being exposed to COVID-19 (2)
- ○ You should wear a face mask around others if you are sick (3)
- ○ If you use hand sanitizer, it should be 95% alcohol (4)

Figure 3.2A. Conditions for Disease Spread Message Experiment.

Close Network Prime (disease spread prime)

Start of Block: Close-Network Prime I

Q1 **You've been randomly assigned to read an excerpt of an article from the New York Times about Covid-19. Please read it and answer the following questions.**

My husband mentioned that his cousin S., who lives far away, would be visiting the area and wanted to come over for dinner in our backyard, and I paused.

"Don't forget, my parents come next week," I said.

But by the time the day came for S.'s visit, the desire for normalcy had pushed past thoughts of safety, and she arrived wearing a mask. She spent the next couple of hours in our backyard eating takeout Thai and talking without a mask. Then she put it back on as she left.

We got the text on the following Tuesday that S., who asked that only her first initial be used, had tested positive for the coronavirus.

It was left to us — the 17 people whom S. had come into direct contact with between the date of the test and the result, and the many more who had come in contact with us and then with others — to do it ourselves. That came to almost 70 people.

It's worth exploring what is happening across the country, and why it is likely to get worse, as schools and churches and bars and restaurants snap open and close while the virus continues to fester. My own family is white and privileged; we have access to doctors and sick days and smartphones. I can't imagine how much worse our situation would be without those things.

prime1_attention According to the article, how many people did S. come into direct contact with between getting a test and getting the test result?

○ 2 (1)

○ 17 (2)

○ 25 (3)

○ 70 (4)

*

prime1_boxes We want to understand your perception of risk in your daily life.
If you were to contract Covid-19, who do you think you're most likely to get it from?

In the boxes below, please list your relationship to 2-5 people who you could catch Covid-19 from (ex. “sister” or “friend”).
Then think about who they could catch Covid-19 from (ex. “friend” or “her husband”).

- ◯ 1a. Who could you catch Covid from? (1) ________________________________
- ◯ 1b. Who might they catch it from? (2) ________________________________
- ◯ 2a. Who could you catch Covid from? (3) ________________________________
- ◯ 2b. Who might they catch it from? (4) ________________________________
- ◯ 3a. Who could you catch Covid from? (5) ________________________________
- ◯ 3b. Who might they catch it from? (6) ________________________________
- ◯ 4a. Who could you catch Covid from? (7) ________________________________
- ◯ 4b. Who might they catch it from? (8) ________________________________
- ◯ 5a. Who could you catch Covid from? (9) ________________________________
- ◯ 5b. Who might they catch it from? (10) ________________________________

End of Block: Close-Network Prime I

Far Network Prime (not analyzed in this study)

Note: This is a secondary control condition that was only included in the disease spread experiment. In this paper, we analyze only the control condition that was common across our *experiments. We do not analyze this condition in the paper because it is beyond the scope of our analysis.*

Start of Block: Far-Network Prime I

Q5 You've been randomly assigned to read an excerpt of an article from the New York Times about Covid-19. Please read it and answer the following questions.

Singapore has seen a surge of coronavirus cases among migrant workers, after months of successfully controlling the outbreak. As of Tuesday, coronavirus cases linked to migrant worker dormitories accounted for 88 percent of Singapore's 14,446 cases, including more than 1,400 new cases in a single day.

Many migrant workers live in packed dormitories on the outskirts of the city. These dormitories can house up to 20 people per room, making it almost impossible to follow social distancing guidelines. Migrant workers around the world have been among the most vulnerable groups affected by the pandemic.

S11, a dormitory with the largest cluster of the coronavirus in Singapore, houses more than 2,200 people who are infected. The dormitory has a capacity of over 10,000.

---

prime2_attention According to the article, what percentage of Covid-19 cases in Singapore are linked to migrant worker dormitories?

○ 10% (1)

○ 27% (2)

○ 55% (3)

○ 88% (4)

Page Break

prime2_boxes We want to understand your perception of risk in your daily life.
If you were to contract Covid-19, who do you think you're most likely to get it from?
In the boxes below, please list your relationship to 2-5 people who you could catch Covid-19 from (ex. "grocery cashier," or "student").
Then think about who they could catch Covid-19 from (ex. "coworker" or "bus passengers").

○ 1a. Who could you catch Covid from? (1) ____

○ 1b. Who might they catch it from? (2) ____

○ 2a. Who could you catch Covid from? (3) ____

○ 2b. Who might they catch it from? (4) ____

○ 3a. Who could you catch Covid from? (5) ____

○ 3b. Who might they catch it from? (6) ____

○ 4a. Who could you catch Covid from? (7) ____

○ 4b. Who might they catch it from? (8) ____

○ 5a. Who could you catch Covid from? (9) ____

○ 5b. Who might they catch it from? (10) ____

End of Block: Far-Network Prime I

Control Condition

Start of Block: Control Condition I

Q8 Please review the following information about Covid-19, excerpted from the CDC.

COVID-19 is a new disease, caused by a novel (or new) coronavirus that has not previously been seen in humans.

Current symptoms reported for patients with COVID-19 have included mild to severe respiratory illness with fever, cough, and difficulty breathing.

The best way to prevent illness is to avoid being exposed to this virus. The virus is thought to spread mainly from person-to-person.

Protect yourself, protect others

Stay home if you are sick, except to get medical care.

Cover your mouth and nose with a tissue when you cough or sneeze or use the inside of your elbow.

Wash your hands often with soap and water for at least 20 seconds especially after you have been in a public place, or after blowing your nose, coughing, or sneezing.

Put distance between yourself and other people if Covid-19 is spreading in your community.

If you are sick: You should wear a face mask when you are around other people and before you enter a healthcare provider's office.

---

control_attention_ch According to the information above, which of the following IS NOT true?

- ○ Covid-19 has not previously been seen in humans (1)
- ○ The best way to prevent illness is to avoid being exposed to Covid-19 (2)
- ○ You should wear a face mask around others if you are sick (3)
- ○ If you use hand sanitizer, it should be 95% alcohol (4)

Page Break

control_boxes
Can you think of other contagious diseases that, like Covid-19, are contagious and spread from person to person? What are their symptoms?

○ Contagious disease #1 (1) ____

○ Symptom (2) ____

○ Contagious disease #2 (3) ____

○ Symptom (4) ____

○ Contagious disease #3 (5) ____

○ Symptom (6) ____

○ Contagious disease #4 (7) ____

○ Symptom (8) ____

○ Contagious disease #5 (9) ____

○ Symptom (10) ____

End of Block: Control Condition I

Figure 3.3A. Conditions for Hardship Message Experiment.

Control Condition

Start of Block: Control Condition

control_condition_1 You have likely heard about COVID-19, the disease caused by coronavirus SARS-CoV-2 (hereafter “covid-19”).
Can you think of other contagious diseases that, like covid-19, are contagious and spread from person to person? What are their symptoms?

Name up to 5 other contagious diseases that spread from person to person, and one symptom of each.

○ Contagious disease 1 (4) ____

○ Symptom (5) ____

control_condition_2 Can you think of another contagious disease?

○ Contagious disease 2 (4) ____

○ Symptom (9) ____

control_condition_3 Can you think of another contagious disease?

○ Contagious disease 3 (4) ____

○ Symptom (9) ____ control_condition_4 Can you think of another contagious disease?

- ○ Contagious disease 4 (4) ____
- ○ Symptom (9) ____

control_condition_5 Can you think of another contagious disease?

- ○ Contagious disease 5 (4) ____
- ○ Symptom (9) ____

Page Break

Q4 **Please review the following information about covid-19, excerpted from the CDC.**

COVID-19 is a new disease, caused by a novel (or new) coronavirus that has not previously been seen in humans.

Current symptoms reported for patients with COVID-19 have included mild to severe respiratory illness with fever, cough, and difficulty breathing.

The best way to prevent illness is to avoid being exposed to this virus. The virus is thought to spread mainly from person-to-person.

Protect yourself, protect others

Stay home if you are sick, except to get medical care.

Cover your mouth and nose with a tissue when you cough or sneeze or use the inside of your elbow.

Wash your hands often with soap and water for at least 20 seconds especially after you have been in a public place, or after blowing your nose, coughing, or sneezing.

Put distance between yourself and other people if COVID-19 is spreading in your community.

If you are sick: You should wear a face mask when you are around other people and before you enter a healthcare provider's office.

According to the information above, which of the following IS NOT true?

- ◯ COVID-19 has not previously been seen in humans (1)
- ◯ The best way to prevent illness is to avoid being exposed to COVID-19 (2)
- ◯ You should wear a face mask around others if you are sick (3)
- ◯ If you use hand sanitizer, it should be 95% alcohol (4)

End of Block: Control Condition

Prime Condition

Start of Block: Prime Condition

prime_condition_1 You have likely heard about COVID-19, the disease caused by coronavirus SARS-CoV-2 (hereafter "covid-19").
Many people have lost their jobs, temporarily or permanently, over the past month due to efforts to combat covid-19. **Can you think of anyone experiencing financial hardship due to covid-**19**, who you'd like to help?**
In the boxes below, please list your relationship to people who are experiencing financial hardship (ex. "mother," "cousin," "friend"), and how they've been affected (ex. "laid off," "reduced wages," "fewer job opportunities").

- ◯ Person you would help 1 (4) ____
- ◯ How have they been affected? (5) ____

prime_condition_2 Who else would you help?

○ Person you would help 2 (1) ____

○ How have they been affected? (2)
____

prime_condition_3 Who else would you help?

○ Person you would help 3 (1) ____

○ How have they been affected? (2)
____

prime_condition_4 Who else would you help?

○ Person you would help 4 (1) ____

○ How have they been affected? (2)
____

prime_condition_5 Who else would you help?

○ Person you would help 5 (1) ____

○ How have they been affected? (2)
____

Page Break

Q8 **Please review the following information about the economic impact of covid**-19 **efforts** (excerpted from The New York Times, originally published April 23, 2020)**.**

Nearly a month after Washington rushed through an emergency package to aid jobless Americans, millions of laid-off workers have still not been able to apply for those benefits — let alone receive them — because of overwhelmed state unemployment systems.

...On Thursday, the Labor Department reported that another 4.4 million people filed initial unemployment claims last week, bringing the five-week total to more than 26 million.

“At all levels, it’s eye-watering numbers,” Torsten Slok, chief international economist at Deutsche Bank Securities, said. Nearly one in six American workers has lost a job in recent weeks.

Delays in delivering benefits, though, are as troubling as the sheer magnitude of the figures, he said. Such problems not only create immediate hardships, but also affect the shape of the recovery when the pandemic eases.

According to the information above, which of the following IS NOT true?

- ○ 26 million people have filed unemployment claims (1)
- ○ Nearly 1 in 6 American workers has lost a job in recent weeks (2)
- ○ Some laid-off workers have not received unemployment benefits (3)
- ○ The article claims it is possible to know when people will return to work (4)

Appendix: Supplementary Materials

Supplementary Materials 3.1A. Pre-registration Materials.

https://aspredicted.org/blind.php?x=/PKN_JZT (registered on (04/03/2020)
https://aspredicted.org/blind.php?x=/TMH_X29 (registered on 05/05/2020)
https://aspredicted.org/blind.php?x=/RTZ_ZP4 (registered on 10/26/2020)

Above are links to our pre-registration documents for peer-review on AsPredicted.org. All pre-registrations took place prior to data collection or access to the data.

CHAPTER FOUR: TO TRUST IN YOURSELF OR OTHERS? A STUDY OF PERSONAL BELIEFS AND SOCIAL PERCEPTIONS ON COVID-RELATED BELIEFS AND BEHAVIORS

Introduction

Making good choices when confronted with uncertain risk is a difficult task. Rational choice approaches are not possible when risks and benefits are unknown, and so people often turn to signals from their social environment. Decision making during the first year of the Covid-19 pandemic is one such environment. During this time, knowledge about the virus grew, policies changed, and the social meanings associated with the pandemic evolved. In the United States, political polarization and judgments about risk are frequent explanations of social behavior during the pandemic (Shin et al., 2021; Kwon, 2022). Fewer studies consider what people perceived in their social environment and how they adjusted their behavior in response.

Many disciplines consider how people make decisions under uncertainty. In behavioral economics, research emphasizes the role of cognitive and emotional factors in biasing judgments of risk and subsequent behavior (Tversky & Kahneman, 1974; Lerner et al., 2015; Fischhoff & Broomell, 2020). Social influence theory proposes people adopt preferences, emotions, behavior, and traits from others in their environment (Spears, 2021). Ecological rationality approaches characterize this as an “imitate the majority” heuristic and shows that conforming to prevalent behaviors can be advantageous (Gigerenzer & Gaissmaier, 2010). Both a person’s personal perceptions and their social environment may explain their behavior.

A person’s personal perception of risk tends not to be completely individual, but instead is often affected by their environment. However, which conditions provoke stronger adherence to one’s social environment remains an open question (Samadipour et al., 2020; Jones et al., 2013; Masuda & Garvin, 2006). It is difficult to disassociate the role of social influence from a person's personal perception of risk, and so few studies consider both simultaneously. However, without doing so, researchers cannot explain why people form beliefs that are very different from others in their social world. By asking what participants thought about other people's judgements, I begin to consider the extent to which people believe they agree or disagree with the perceived majority.

My work advances understanding of risk perception and decision making by differentiating between personal risk perceptions and perceptions of other people's judgements. I explore how such personal and social perceptions differently inform three health behaviors that have varying personal costs and benefits: protective behavior, vaccination, and data sharing. Many models assume the health behavior people practice is driven primarily by their interest in their own health. Understanding the extent to which peoples' health behavior is also shaped by social rewards can lead to interventions that target the many causes of behavior.

Background

Responding adequately to Covid-19 required persuading ordinary people to change their daily behavior. Many cognitive and environmental mechanisms could encourage these changes (Van Bavel et al., 2020; West et al., 2020). This includes social context, which should not be overlooked in explanations of social behavior (Holtz et al., 2020; Coroiu et al., 2020). I consider two signals from one's social context — social perceptions of disease prevalence and perceived stigma — to strengthen our understanding of how one's social context affects behavior.

Risk Perception, Judgment, And Decision Making

A great deal of research on risk perception, judgment, and decision making focuses on human cognition. Foundational work showed cognitive biases result in suboptimal or irrational decision making (Tversky & Kahneman, 1974; Kahneman & Tversky, 1979). Work in behavioral economics has sought to describe the situations people face, how they tend to respond to them, and understand how interventions can create more optimal decision making (Fischhoff & Broomell, 2020). Development of this field has led to the consideration of additional factors that weigh on our decisions. These include emotion (Lerner et al., 2015) and social context (Gigerenzer & Gaissmaier, 2010).

The ecological rationality paradigm is especially relevant to this study (e.g. Marsh, 2002; Todd & Gigerenzer, 2012). It studies heuristics, which are strategies that enable quick decision-making by focusing on some available information and ignoring other information. Ecological rationality contends that to evaluate human decision making, researchers should consider how optimally a heuristic matches the context a person applies it to. The observation that strategies are related to environments motivates us to understand the social environments respondents perceive in this study.

Studies of behavior in the Covid-19 pandemic have identified individual factors that affect behavior, though they tend not to consider the interplay between individual factors and environment. Common theoretical models of health behavior emphasize a person's individual motivation to perform the behavior (West et al., 2020), and their beliefs about the behavior (Janz & Becker, 1984). It is unsurprising, then, that much research about behavior in the Covid-19 pandemic focuses on peoples' motivations (Coroiu et al., 2020; Jordan et al., 2021; Oosterhoff et al., 2020) and beliefs (Zampetakis & Melas, 2021; Clark et al., 2020). However, the mechanisms these studies identify, like altruism and risk tolerance, have not consistently explained health behavior during the Covid-19 pandemic (Sheth & Wright, 2020). Other subconscious processes may help explain health behavior, such as working memory capacity (Xie et al., 2020), emotions (Renström & Bäck, 2021), and morality (Chan, 2021; Byrd & Bialek, 2021).

A key factor in explanations of health behavior is perception of risk (Brewer et al., 2007; Sheeran et al., 2014). Studies found perceptions of risk predicted Covid-19 related health behavior (Chan et al., 2020; Wise et al., 2020; Lunn et al., 2020; Brown et al., 2021). However, information about Covid-19 risks was quite uncertain during the first year of the pandemic. Public knowledge about the virus developed as the virus spread, and people lacked information about their local risk because of the virus's multi-day incubation period and the prevalence of asymptomatic cases. Perception of risk may therefore vary from person to person due to experience with Covid-19 and susceptibility to severe illness (Laires et al., 2021), as well as social factors like political identification, prosocial values, and belief in collective efficacy (Dryhurst et al., 2020). Perception of Covid-19 risk, as well as these contextual features are likely to be factored into the estimates of how much Covid-19 would spread across the population. This leads to my first hypothesis:

H1: Personal estimates of population prevalence will be positively associated with likelihood to practice protective behavior, vaccination, and data sharing.

Social Influence

Why did groups of people in the U.S. hold such different perceptions of risk in such a short period following the beginning of the Covid-19 pandemic? Sociological theory contends that social dynamics bias the ways people learn information and adopt heuristic strategies, resulting in different behaviors across social groups (Lamont et al., 2017; Vaisey & Valentino, 2018; Bruch & Feinberg, 2017). Political partisanship is the most-studied example of the phenomenon in the Covid-19 pandemic (e.g. Green et al., 2020; Allcott et al., 2020). However, partisanship does not fully explain behavior in the Covid-19 pandemic. Capturing additional information about what a person perceives from their social context may help explain their responses.

Social influence is a particularly impactful mechanism that explains a variety of behaviors and beliefs (Spears, 2021). However, it may be incorrect to assume an overly-rational model of social influence. The reason social influence is effective could be that it helps people make beneficial choices about risk, or that people gain social rewards for conforming to norms (Spears, 2021; Enemark et al., 2014). Perceptions mediate social influence. As people copy what they perceive of their social environment, they might copy what their peers are doing, or they might only copy what they think their peers are doing (Van Bavel et al., 2020). It is not necessarily true that people copy their environment to optimize the outcomes that are directly affected by the behavior.

People tend to be especially attentive to the behavior of their reference groups in times of rapid change (Kelley & Evans, 2017). Social expectations may become unclear as one's context shifts rapidly, and so looking to others may be one of few options to make sense of change — even if this leads to distorted beliefs or suboptimal behavior. Research confirms social cues are an important explanation of behavior in the Covid-19 pandemic. Social cues affect likelihood to practice protective behavior (Horne & Johnson, 2021; Tunçgenç et al., 2021), willingness to share data (Oldeweme et al., 2021), and intent to get vaccinated (Winter et al., 2021). However, some suggest the effect of behavioral norms on health behavior may be limited due to free-riding (Ibuka et al., 2014) or cultural tendencies to practice prosocial behavior (Bellato, 2020).

A person's social environment affects the risks they perceive. For example, studies of social networks find who a person is connected to is significantly associated with risk perceptions (Scherer & Cho, 2003; Kohler et al., 2007; Koku & Felsher, 2020). Scholars suggest this is because people co-create similar perceptions of risk. Culture also affects how people communicate about risk, which then modifies risk perceptions (Masuda & Garvin, 2006; Jones et al., 2013). However, which conditions increase or decrease the effect of social context on risk perceptions is not fully understood (Samadipour et al., 2020; Jones et al., 2013). This research tends to focus on physical risks such as the risk of HIV transmission. Fewer studies consider how risks of physical and social harm may affect decision making.

Perceptions of risk and perceptions of one's social environment mutually shape each other, and so they are difficult to disassociate. People tend not to know how much they are influenced by others, and how much of their thinking is truly their own. Directly asking people about the role of social influence in their lives is unlikely to yield meaningful information. To this end, I borrow insights from the "surprisingly popular" method that was developed to elicit correct predictions from group surveys (Prelec et al., 2017). In addition to asking for the respondents' own answer to questions (i.e. "what do you think the correct answer is"), the surprisingly popular method also asks the respondents to guess what they expect the most common answer would be from the general public. This procedure yields a quantifiable measure of the perceived discrepancy of one's "personal" judgment and the "general public". Research using this method (Rutchick et al., 2020) suggests it is an effective technique to distinguish between what people believe and what they perceive in their environment.

H2: Social perceptions of prevalence will be positively associated with likelihood to practice protective behavior, vaccination, and data sharing.

A person's tendency to conform may moderate the effect of social influence on their behavior, and this tendency may vary throughout the population (Efferson et al., 2008). Social influence affects behavior through descriptive and prescriptive norms (Schultz et al., 2007).

People who seek the approval of others are more likely to be attentive to norms and to the behavior of others.

Conformity may also depend on reference group. People tend to trust information from members of their in-group, and are motivated to agree, collaborate, and cooperate with them (Haslam & Reicher, 2017). Simultaneously, people may be motivated to act in opposition toward their out-groups (Iyengar et al., 2019). In-group conformity and out-group avoidance may be especially heightened during health emergencies (Wu & Chang, 2012; Griskevicius et al., 2006). Some cite this dynamic to explain differences between Democrats and Republicans in the practice of protective behavior (Allcott et al., 2020), support for surveillance (Zhang et al., 2020), rates of vaccination (Ye, 2021) and other Covid-19 policy preferences (Gadarian et al., 2021).

H3: Individual tendency to conform will moderate the effect of social perceptions of prevalence on protective behavior, vaccination, and data sharing.

Social stigma is an additional element of social context that may affect Covid-19 behavior. Having a stigmatized condition can be deeply discrediting (Goffman, 1963; Pescosolido & Martin, 2015). Social stigma is unfortunately common in disease epidemics. It can encourage patients to conceal their symptoms, lead to discrimination toward patients and social groups associated with the disease, and create adverse mental health effects (Yuan et al., 2021). If Covid-19 is stigmatized, contracting it carries social risk in addition to health risks. People may be motivated to avoid social stigma as much as they are motivated to avoid illness. However, avoiding stigma and avoiding illness may create conflicting goals. For example, sharing health information can strengthen public health surveillance but also increase a person's risk of reputational harm. Past research finds people with stigmatized conditions especially value privacy to maintain social standing (Anthony et al., 2017). Thus, stigma may differently affect different health behaviors.

H4: Perceived stigma of Covid-19 will be positively associated with likelihood to practice protective behavior and vaccination, but may be negatively associated with support for data sharing.

Present Study

I analyze how personal perceptions of disease prevalence ("personal perceptions") and the perceptions respondents believe *others* hold ("social perceptions") are associated with three different behaviors meant to intervene in the Covid-19 pandemic. People vary in their tendency to conform, and so I consider whether the effect of social perceptions varies by a person's tendency to conform. Finally, I consider perceptions of social stigma to understand whether the actions people take are explained by the *social* risks and benefits they perceive. As mentioned above, explanations of behavior in the Covid-19 pandemic tend to focus on polarization and perceived disease risk, and behavioral interventions tend to provide information and emphasize altruism. My goal is to consider whether social perceptions and social risks also affect how people respond to this pandemic. I analyze surveys of the US adult population collected during 2020. I find each health behavior is differently associated with personal perceptions, social perceptions, and stigma. I conduct a second analysis to explore the factors that are associated with having large differences in personal and social perceptions of risk.

Methods

Data Collection

Data for this analysis was collected in four waves over the course of 2020: April 3–8 (n=97), May 1–May 11 (n=142), October 19–28 (n=214), and November 20–25 (n=197). The panel provider Qualtrics recruited respondents for this research. All respondents were over the age of 18. The sample also imposed quotas for gender (50% male, 50% female), race (~66% non-Hispanic white, ~12% black, ~12% Hispanic, ~10% other), and education (50% some college or less, 50% associates and above). The survey used attention and consistency checks to ensure respondents read the material and gave consistent answers. Qualtrics verifies the identity of respondents to prevent a single person from holding duplicate accounts. All variables are self-reported by respondents. The survey data was collected from 4 experiments. The mean and standard deviation of each regression variable used in this analysis and each experimental condition are shown in Table 4.1A. This research was approved by the Institutional Review Board (IRB) of UCLA, which granted a waiver of informed consent for this research.

Outcome Measures

The regression analysis models three different types of health behavior: protective behavior (e.g. masking, physical distancing), support for data sharing policies, and intent to take a vaccine.

Protective Behavior. Respondents were asked how likely they were to practice several protective behaviors. Responses were measured using a five point Likert scale. In the survey conducted during April 2020, respondents were asked to rate the likelihood of doing each of the following if they exhibited symptoms of Covid-19: wear a face mask, self-isolate, and encourage others to stop the spread. In the surveys conducted during May through November, respondents were asked how likely they were to wear a face mask, step away if someone stood near them, and avoid crowded places. The difference between the first and subsequent waves of the survey reflects differences in context (e.g. whether lockdowns were common) and common knowledge about Covid-19 at the time of the survey. The health behavior variable is calculated by summing the respondent's answer to each question and standardizing responses. The scaled variable has a range of -4.03–0.91. Scaled variables were calculated separately for the first wave of data collection because of the difference in questions.

Data Sharing. This variable measures how strongly respondents agreed or disagreed with their own data being collected for various kinds of surveillance. It was measured using a 5-point Likert scale. The questions were as follows:

Public health authorities should access location data from phones to see if people are following stay-home orders.

- If I am diagnosed with covid-19, public health authorities should make my name public so others can know if they've been exposed.
- If I am diagnosed with covid-19, public health authorities should make the places I have been in the past five days public so others can know if they've been exposed. For example, through a phone app that other people can download.
- If I'm ordered into self-quarantine, I should be required to wear a wristband that tracks my movements.
- Public health authorities should NOT be allowed to publish information that allows me to be identified.

These questions are drawn from policies discussed or adopted in China, South Korea, Singapore, and the United States by the end of March 2020. Many of these measures violate privacy norms in the United States, where I collected the data. At the time of the survey I assumed most respondents would agree to cooperate with traditional contact tracing efforts, and so I focused on more extreme data sharing policies to better measure variation in opinions. The effectiveness of these policies is debated (Sonn & Lee, 2020; Whitelaw et al., 2020; Calvo et al., 2020; Munzert et al., 2021).

Each respondent's responses were summed and scaled using the same method as the protective behavior variable. Responses to the question "public health authorities should NOT be allowed to publish information that allows me to be identified," were reversed. High scores indicate a high willingness to share data at the expense of privacy, low scores indicate a high support of privacy at the expense of disease surveillance. The range of the standardized variable is -1.76–2.097.

Vaccination Intent. Respondents were asked how strongly they agreed on a 5-point Likert scale with the following question: "I plan to get vaccinated for COVID-19 when a vaccine is approved by the FDA." This question was only included in the surveys conducted in October and November of 2020. At the time of both surveys, vaccine candidates were in clinical trials and had not yet been endorsed by the FDA. Pfizer/BioNTech published results showing their vaccine was 95% effective between the October and November waves of the survey, which likely contributes to the increase in intent to take a vaccine between October and November (see Figure 4.1A).

Regression Covariates

Personal Perceptions of Prevalence. Respondents were asked: "What % of people in the United States will get coronavirus by the end of this year?" Respondents were given a sliding scale set at 50% as the default, and were required to interact with the slider to continue the survey. A separate page of the survey asked what percentage of the US population respondents expected to NOT contract Covid-19 by the end of 2020. Responses to these questions were summed, and only respondents whose answers summed to between 80–120% were included in the analysis. This ensures respondents in this study gave internally consistent responses. This question measures only one dimension of risk perception (Vieira et al., 2021). However, it was possible for all respondents to answer throughout the pandemic regardless of their personal experience of Covid-19 and their true level of risk. Given that as many as one in three Americans contracted Covid-19 during 2020 (Sen et al., 2021), it was important to use a measure of risk that could be fairly compared across respondents and measured consistently throughout the pandemic.

Social Perceptions of Prevalence. Respondents were asked the following question immediately after the personal perception of prevalence question: “Think about other people’s beliefs. What do you think the average answer is?” This adopts the question structure of the surprisingly popular method, and allows us to measure what respondents think others believe.

Perceived Stigma. Perceived stigma is what a person believes others associate with an illness or characteristic. To measure perceived stigma of Covid-19, I asked respondents how much they agreed on a Likert scale from 1–5 with the following question: “I think other people might talk down to me if they knew I had Covid-19.” This question has been used to measure stigma of other kinds of illness (King et al., 2007).

Tendency to Conform. I measured a respondent’s tendency to conform by asking how well three statements from the self-monitoring scale described them (Lennox & Wolfe, 1984). Responses were summed to create a single variable. The statements are as follows:

- I tend to show different sides of myself to different people.
- When I am uncertain how to act in a social situation, I look to the behavior of others for cues.
- In different situations and with different people, I often act like very different persons.

Party ID. I used the partyid question from the General Social Survey to collect information about respondents' political affiliations. Binary variables for Republicans and Independent/Other respondents were created by grouping respondents who identified as Republicans or as Republican-leaning into one category, and respondents who identified as wholly independent of "other" into a second category. Respondents who identify as Democrats or as Democrat-leaning are the reference category in this regression analysis.

Additional Variables

Estimate Difference. I calculated the difference between respondents' personal and social perceptions by subtracting a respondent's personal perception from their social perception. Positive values indicate the respondent expects others to overestimate the future prevalence of Covid-19 relative to their own beliefs, and negative values indicate the respondent expects others to underestimate the future prevalence of Covid-19 relative to their own beliefs.

Race. The race variables are self-identified and not mutually exclusive.

Education. Respondents are grouped by their highest level of education: a high school diploma, an associate's degree or some college, a bachelor's degree, or a graduate degree.

Math Accuracy. Respondents to the April and May waves of the survey were asked to answer three math problems. The questions varied in difficulty, but all could be solved with simple addition, multiplication, and division. Accuracy is measured by how many questions respondents answered correctly. See Supplementary Information section of the Appendix for question information.

Policy Preference. Respondents in the April, May, and November survey waves were asked whether they believed stay home orders adopted by many cities and states went too far, seemed appropriate, or needed to go further. There were few stay home orders in the US during

October, and so it was omitted from the survey. Due to the evolving nature of the pandemic, the wording of the question varied during each wave. However, the response choices were consistent. See Supplementary Information section of the Appendix for question wording.

Racism and Xenophobia. Respondents surveyed between October and November 2020 answered the explicit racial resentment scale (Wilson & Davis, 2011) and seven questions to measure xenophobia (Chapman Survey, 2014). Scales were reversed where relevant such that higher values indicate higher levels of xenophobia or racism. Responses were summed to create a single measure.

Statistical Analyses

In the first section of my analysis, I use general linear regression models to examine the relationship between health behaviors and perceptions. In the second section of my analysis, I use t-tests and the Pearson correlation coefficient to explore socio-demographic correlates of the personal and social risk perception differential.

Results

This research analyzes how likely people are to adopt three different health behaviors depending on their own perceptions of disease prevalence ("personal perception"), and their perceptions of how prevalent other people think Covid-19 is ("social perception"). Though personal estimates and social estimates mutually affect each other, they are only moderately correlated $r(649) = 0.445$, $p = 0.000$. Tables 4.1–4.3 show the results of OLS regression models with standardized coefficients for these three outcome variables: protective behavior, support for data sharing, and intent to vaccinate.

If a person's perception of risk affects their behavior, we should expect their personal perception to strongly predict each health behavior (H1). Table 4.1 shows protective behavior is significantly associated with personal perception. The estimate of model 1 is not improved by adding additional controls for perception of stigma or tendency to conform, nor with the interaction between social perception of prevalence and tendency to conformity.

Which factors predict likelihood to get vaccinated are quite different from those that predict protective behavior. There is no significant association between personal perceptions and likelihood to get vaccinated in models 4.1–4.3. In contrast, higher social perceptions are significantly associated with lower intent to get vaccinated. This is contrary to my hypothesis. The interaction between social perceptions and conformity shows there is a different effect of social perceptions depending on a person's tendency to conform. (see Figure 4.1, panel 2 for illustration). Among the least-conforming respondents, higher social perceptions are associated with a lower likelihood of getting vaccinated. These respondents act contrary to the social perception they hold, perhaps because they perceive others exaggerate the risk of Covid-19. Among the most-conforming respondents, higher social perceptions are associated with higher likelihoods of getting vaccinated. These respondents are acting in-line with the expectation that people treat social perceptions as heuristics to assess risk.

Also in line with my expectation, people who perceive Covid-19 as more stigmatized are significantly more likely to take a vaccine after controlling for other factors (H4). One reason people adopt the behavior of the majority is because fitting in is often socially beneficial, and standing out can be socially harmful. I expect people who perceive Covid-19 as more stigmatized go to greater lengths to avoid contracting it in part to preserve their social status.

Support for data sharing is predicted both by personal perceptions and multiple social variables. Personal perceptions are positively associated with likelihood to share data throughout the model. Social perceptions are only predictive of data sharing in the final model, after controlling for its interaction with conformity. The association between social perceptions, conformity, and my outcome variable is consistent with their effect in Table 4.2. People who are more conforming are *more* likely to share data the higher their social perceptions. People who are less conforming are *less* likely to share data the higher their social perceptions (see Figure 4.1, panel 3 for illustration). The F-test indicates the model is significantly improved by controlling for the interaction between social perceptions and conformity.

Contrary to my expectation (H4), respondents who perceived Covid-19 as more stigmatized were more supportive of data sharing, even after controlling for personal perceptions. I expected the opposite because sharing data creates greater risk of harm to one's reputation. This is especially surprising because four of the five questions in this measure explicitly ask if the respondent themselves would support being surveilled in various ways.

The main analysis finds respondents' personal perceptions and social perceptions differently affect three health behaviors. In the section that follows, I consider why personal and social perceptions vary. Specifically, I explore which sociodemographic variables are associated with the difference between personal and social perceptions ("estimate difference"), how much they tend to differ, and whether respondents tend to expect others to over- or underestimate future disease prevalence.

This analysis suggests gender and education are the most predictive demographic factors (Figure 4.2). Men held higher social perceptions than their personal perceptions on average compared to women. There is a linear trend by level of education and estimate difference, where respondents with higher levels of education held higher social perceptions than their personal perceptions. This indicates men and people with higher levels of education tend to believe others overestimate the future prevalence of Covid-19. I find no significant differences in estimates by respondent age or race.

Interestingly, mathematical ability does not follow the same linear pattern as level of education. Respondents who answered zero math questions correctly tended to hold lower social perceptions than personal perceptions, meaning they tended to expect others to underestimate the future prevalence of Covid-19. Respondents who answered one or more math questions correctly tended to expect others to overestimate the future prevalence of Covid-19. However, the mean difference for respondents who answered all three questions correctly was lower than the mean difference for respondents who missed just one question.

I also find differences in how estimates correspond to politics. Republicans tended to hold much higher social perceptions than personal perceptions compared to Democrats. Respondents with low scores of racism and xenophobia tended to hold lower social perceptions than personal perceptions, while respondents with high levels of racism and xenophobia tended to hold higher social perceptions than personal perceptions. These perceptions are also related to policy preferences. People who believed stay home orders went too far tended to hold higher social perceptions than personal perceptions compared to people who believed the same policies were fine or should go further. However, the causal relationship between political variables and estimate differences are not clear from this data.

This analysis suggests multiple factors contribute to how closely a person's personal perceptions of risk and social perceptions of risk align. Politics, gender, and education are associated with large estimate differences.

Discussion

This study compared the effects of social and personal perceptions of future disease prevalence on three different types of health behavior during the Covid-19 pandemic. I find these behaviors are differently predicted by personal perceptions, social perceptions, and other social factors. That beliefs about one's social environment interact with conformity to predict different likelihoods of adopting some health behavior indicates that fostering a sense of public urgency can encourage some people to adopt public health promoting behavior, but the same sense of urgency can backfire among people who tend not to conform.

I considered how stigmatized respondents perceived Covid-19 to be to evaluate whether respondents respond to risk to their reputation in addition to risk to their health. Indeed, I find higher levels of perceived stigma are associated with higher likelihood to get vaccinated and share data. This suggests that when people make decisions about health behavior, they do not necessarily optimize for expected health outcomes alone. They may adopt or refuse behavior to manage their social standing. Studies of risk behavior can benefit from including measures of perceived social risk to better account for the social consequences people consider as they make decisions. Accounting for perceived social consequences can also help explain why people responded to the pandemic in varied ways.

One motivating factor is seeking the approval of others. Prior experimental work found prescriptive norms (what others approve of) have a stronger effect on behavior than descriptive norms (what others do) (Schultz et al., 2007). The finding that people respond in part to what others think, even when it conflicts with their own perceptions, is consistent with the role of prescriptive norms. Though additional measurement would be necessary to control for the role of descriptive norms, this finding contributes to literature that suggests prescriptive norms are important predictors of risk.

However, I find the way people respond to signals from their social environments varies by a person's tendency to conform, even after controlling for political ID. This underscores the importance of the social and psychological context polarization of behavior occurs within. Prior research shows acting in opposition to out-groups motivates behavior just as strongly as acting in cooperation with in-groups (Iyengar et al., 2019). Having exaggerated perceptions of out-group beliefs can lead a person to become more socially isolated from their out-groups, and can lead them to become more supportive of extreme action (Moore-Berg et al., 2020). I am unable to test the extent to which homophily and partisanship affect what people perceive of their social environment. However, this research does suggest having exaggerated perceptions of others is associated with contrarian behavior among people who tend not to conform. This observation may help to explain why behavior across political groups is varied even when a given behavior is politicized.

A limitation of this study is that it does not include information about the reference groups respondents imagined as they shared their personal perceptions. I cannot analyze the extent to which a respondent's behavior is polar to their out-group and similar to their in-group. Future research can address the hypotheses I suggest by exploring the relationship between reference groups and perceptions of the general population. Doing so can allow for better measurement of whether the effects I find are truly driven by respondents' personal tendencies to conform, or whether respondent social perceptions were differently correlated with more extreme in- and out-group perceptions.

The finding that stigma is positively associated with support for data sharing is surprising. Having a stigmatized illness is socially damaging, and people with concealable stigmatized illnesses tend to value having privacy (Stablein et al., 2015). Further work is needed to explain the relationship I find between perceiving Covid-19 as more stigmatized and supporting reductions of privacy. It may be that believing Covid-19 is very serious is a confounding factor that increases both perceptions of stigma and support for data sharing independently. Other possible explanations are that respondents did not believe the data sharing policies in the survey were risky for stigmatized people (Barth & de Jong, 2017), or that respondents did not expect to contract Covid-19 and held negative feelings toward people who they expected to contract Covid-19 (Herek et al., 2003). This apparent conflict may be related to explanations of the privacy paradox — the tendency for people to say they highly value privacy but give away personal information for little gain — in other contexts (Kokolakis, 2017).

I also explored the extent to which having distinct social and personal perceptions varied by demographic and attitudinal factors. The findings are consistent with past research that finds these factors help explain differences in whether a person agrees with what they perceive from their social environment (Salazar et al., 2012; Flache et al., 2017). Future work should explore the mechanisms of polarization that lead some groups to maintain different social and personal perceptions. It may also explore whether similar social and personal perceptions are the result of people adopting their social perceptions, or people selectively perceiving signals from their environment that are more like their own beliefs.

This study has two important limitations. First, this analysis is correlational and so I cannot determine causality among these variables. This is important because, though theoretical models tend to emphasize the effect of risk perception on action, action can also shape risk perception (Qin et al., 2021). Additional research is necessary to ascribe causal effects and determine effective interventions.

Second, data sharing and vaccination were hypothetical actions to respondents at the time of the survey, while protective behaviors were mandated or strongly encouraged. People report hypothetical behavior differently than their actual behavior (Penn & Hu, 2018). Additional research is needed to determine if the association between social factors and health behavior is caused by differences in the social meanings ascribed to different behaviors, or by the realism of the behavior to respondents. Further exploration of this limitation will still yield insight for public health. For example, future work may find perceptions of one's social environment are especially important predictors of behavior during the early stages of interventions, or are consistently more important predictors of some behaviors than others.

Tables

Table 4.1. Impact of Perceptions on Protective Behavior (n=650).

	Personal Perception of Risk Only	Social Perception of Risk Only	Model 1: Risk Perceptions and Political ID	Model 2: Stigma and Conformity	Model 3: Conformity and Social Signal Interaction
Personal Perception of Risk	0.120 **		0.119 **	0.119 **	0.120 **
Social Perception of Risk		0.012	-0.017	-0.020	-0.118
Republican			-0.258 ***	-0.252 ***	-0.253 ***
Independent			-0.172 ***	-0.163 ***	-0.162 ***
Stigma				0.039	0.039
Conformity				0.068	-0.014
Conformity * Social Perception of Risk					0.141
Intercept	0	0	0	0	0
F-Test				F=2.124, p=0.1204 (compared to model 1)	F=1.2598 p=0.2621 (compared to model 2)

† $p < 0.10$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$. Regression includes controls for age and sex not shown in table. Regression reported with standardized coefficients.

Table 4.2. Impact of Perceptions on Intent to be Vaccinated (n=411).

	Personal Perception of Risk Only	Social Perception of Risk Only	Model 1: Risk Perceptions and Political ID	Model 2: Stigma and Conformity	Model 3: Conformity and Social Signal Interaction
Personal Perception of Risk	-0.019		0.097 † (p=0.086)	0.081	0.080
Social Perception of Risk		-0.110 *	-0.136 *	-0.124 *	-0.322 **
Republican			-0.101 † (p=0.056)	-0.091 † (p=0.082)	-0.087 † (p=0.096)
Independent			-0.188 ***	-0.178 ***	-0.174 ***
Stigma				0.120 *	0.123 *
Conformity				0.079	-0.090
Conformity * Social Perception of Risk					0.297 † (p=0.054)
Intercept	0.000	-0.007	-0.014	0.004	0.006

F-Test		F=4.3972 p=0.01291 (compared to model 1)	F=3.7401 p=0.05383 (compared to model 2)

† $p < 0.10$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$. Regression includes controls for age and sex not shown in table. Regression reported with standardized coefficients.

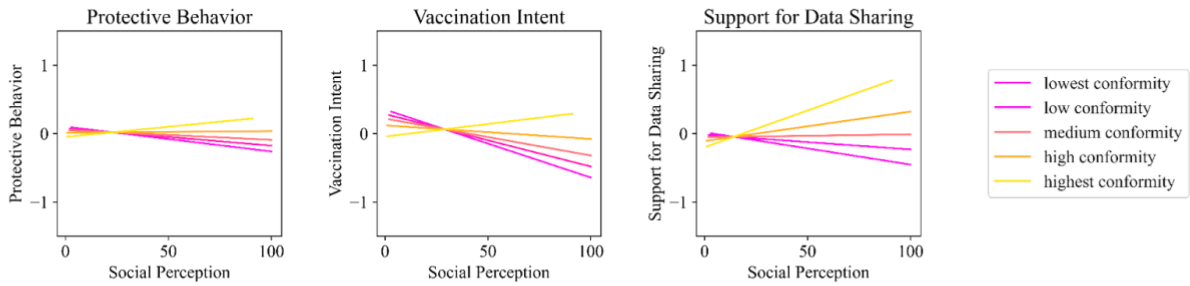
Table 4.3. Impact of Perceptions on Support for Data Sharing (n=650).

	Personal Perception of Risk Only		Social Perception of Risk Only	Model 1: Risk Perceptions and Political ID		Model 2: Stigma and Conformity		Model 3: Conformity and Social Signal Interaction	
Personal Perception of Risk	0.084	*		0.107	*	0.106	*	0.109	*
Social Perception of Risk			0.060	0.024		0.019		-0.216	*
Republican				-0.228	***	-0.215	***	-0.216	***
Independent				-0.216	***	-0.196	***	-0.192	***
Stigma						0.118	**	0.119	**
Conformity						0.148	***	-0.051	
Conformity * Social Perception of Risk								0.338	**
Intercept	0		0	0		0		0	
F-Test						F=13.41, p=0.000 (compared to model 1)		F=7.7872 p=0.005419 (compared to model 2)	

† $p < 0.10$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$. Regression includes controls for age and sex not shown in table. Regression reported with standardized coefficients.

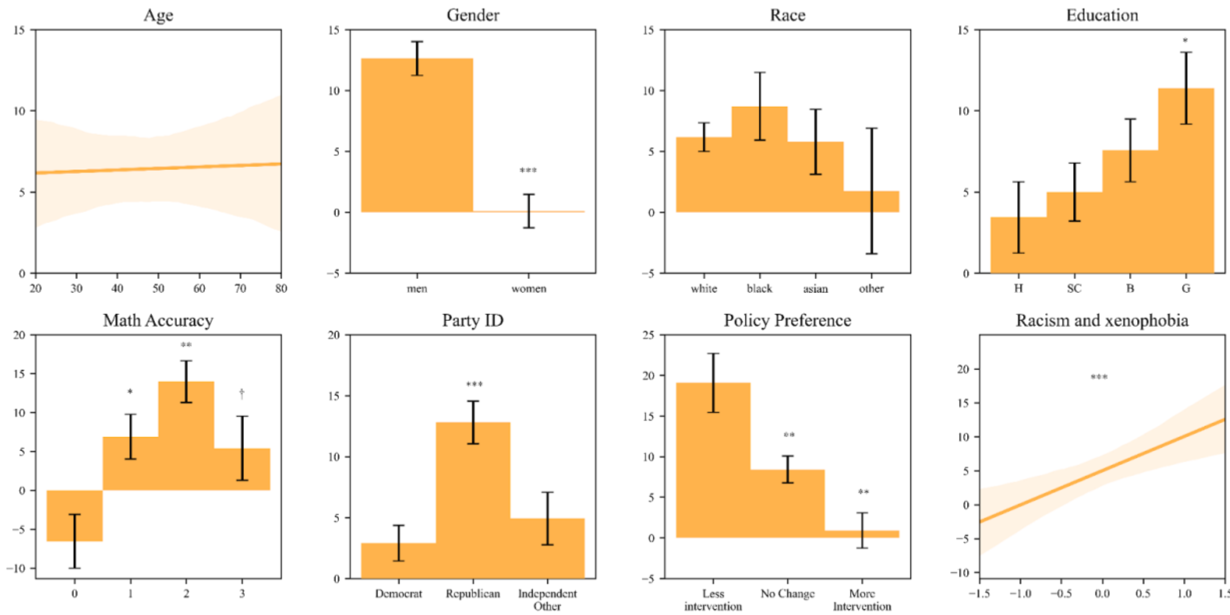
Figures

Figure 4.1. Regression Lines for Each Health Behavior by Social Perception and Level of Conformity.



Regression lines were calculated with standardized coefficients for the modal party ID (Democrat), 50th percentile personal perception (34), and 50th percentile perceived stigma (3).

Figure 4.2. Average Difference Between Personal Perceptions and Social Perceptions by Demographic and Attitudinal Variables.



† $p < 0.10$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$. Y-axis shows estimate difference. Plot titles correspond to x-axis values. Respondents with an estimate difference greater than 0 perceive others have higher estimates of risk than their own. Respondents with an estimate difference lower than 0 perceive others have lower estimates of risk than their own. Bars show standard error of the mean.

Appendix: Tables

Table 4.1A. Mean and Standard Deviation of Dependent Variables by Month and Experimental Condition.

	Health Behavior		Data Sharing		Vaccination	
	Mean	SD	Mean	SD	Mean	SD
April	0.000	1.005	0.080	0.935		
Control	-0.039	0.952	-0.170	0.976		
Prime	0.042	1.068	0.345	0.820		
May	0.101	0.941	0.192	1.059		
Control	0.160	0.847	0.293	1.074		
Prime	0.038	1.035	0.085	1.040		
October	-0.054	1.062	-0.132	0.994	3.523	1.417
Control	-0.340	1.262	-0.316	0.977	3.393	1.358
Prime 1	0.133	0.927	-0.104	0.995	3.573	1.491
Prime 2	-0.044	1.003	-0.026	0.999	3.566	1.389
November	-0.014	0.974	-0.035	0.979	3.726	1.373
Control	0.308	0.670	-0.128	1.044	4.087	1.262
Prime 1	-0.108	1.014	0.013	0.930	3.633	1.360
Prime 2	-0.117	1.056	-0.026	0.999	3.597	1.431

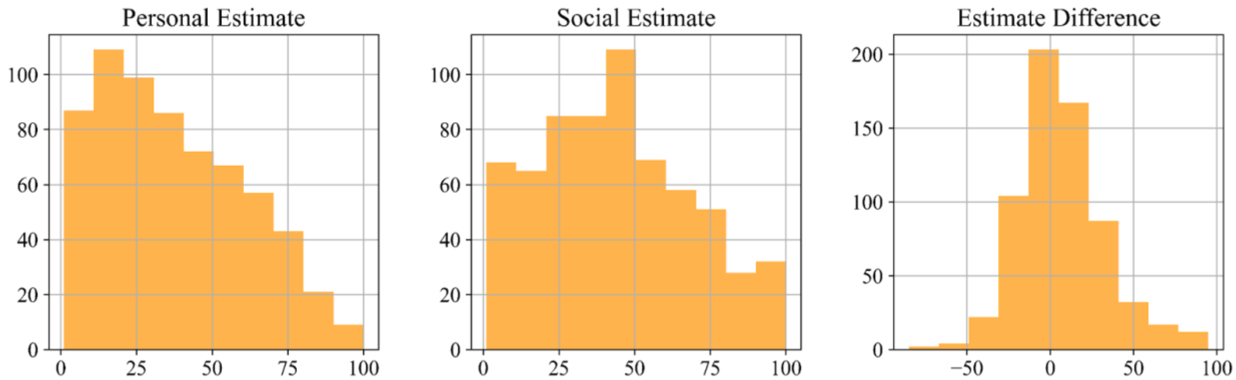
The table above shows the mean and standard deviation for each month we conducted the survey (in gray) and each experimental condition we tested for each month (in white).

Table 4.2A. 95% Confidence Interval by month & prime condition for independent variables.

	Prevalence Estimate		Social Signal		Perceived Stigma		Conformity	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
April	39.845	22.222	45.299	22.273	3.237	1.405	7.330	3.105
Control	41.720	22.667	46.500	21.498	3.120	1.507	7.420	3.111
Prime	37.851	21.802	44.021	23.234	3.362	1.293	7.234	3.129
May	37.261	20.161	48.352	22.680	3.197	1.440	8.324	3.726
Control	38.890	20.057	47.699	22.455	3.219	1.465	8.397	3.836
Prime	35.536	20.272	49.043	23.060	3.174	1.424	8.246	3.632
October	36.565	23.250	40.944	26.053	2.738	1.335	7.196	3.259
Control	29.821	22.053	36.518	25.628	2.393	1.231	6.357	3.344
Prime 1	41.793	21.927	44.549	25.900	2.829	1.395	7.659	3.375
Prime 2	35.895	24.393	40.316	26.313	2.895	1.312	7.316	2.981
November	39.604	26.555	45.330	26.527	2.736	1.325	7.467	3.194
Control	35.565	25.453	37.370	25.630	2.565	1.259	6.891	2.854
Prime 1	42.215	27.151	49.532	26.424	2.848	1.415	7.519	3.254
Prime 2	39.319	26.606	45.806	26.423	2.722	1.270	7.778	3.324

Appendix: Figures

Figure 4.1A. Distribution of Personal Estimate, Social Estimate, and Estimate Difference Variables.



Appendix: Supplementary Material

Wording of Policy Preference Question

April: In response to coronavirus, some cities and states have ordered citizens to stay home, and leave only for essential trips. In your opinion, do such measures go too far, seem appropriate, or should go further?

May: In response to covid-19, cities and states in the US have adopted stay-home orders. In your opinion, do such measures seem appropriate for the country overall? Do they go too far, seem appropriate, or should they go further?

November: In response to an uptick in Covid-19 cases, cities and states in the US have adopted new stay-home orders. In your opinion, do such measures seem appropriate for the country overall? Do they go too far, seem appropriate, or should they go further?

Wording of Math Questions

Question 1, asked as a write-in question:
If person A's chance of getting a disease is 1 in 100 in ten years, and Person B's risk is double that of A, what is B's risk? ____ in 100

Question 2, asked as a write-in question:
The chance of getting a viral infection is 0.0005. Out of 10,000 people, about how many of them are expected to get infected?

Question 3, multiple choice:
One out of every 1000 Americans has disease X. A test has been developed to detect when a person has disease X. Every time the test is given to a person who has the disease, the test comes out positive. But sometimes the test also comes out positive when it is given to a person who is completely healthy. Specifically, out of every 1000 people who are perfectly healthy, 50 of them test positive for the disease.

Imagine we have assembled a random sample of 1000 Americans. They were selected by lottery. Those who conducted the lottery had no information about the health status of any of these people.

Given the information above, on average, what percent of people who test positive for the disease actually have the disease?

a. 5%
b. 2%
c. 95%
d. 50%

CHAPTER FIVE: CONCLUSION

Privacy is an aspect of relationships that may be respected or compromised. As relationships among people change — via new systems, technologies, or priorities — does the meaning of privacy change? Do social relationships still matter as technology plays a greater role in the privacy people have? This dissertation explored the extent to which privacy changed in discourse over the long term as technological privacy became a greater focus, and how public opinions changed over the short term as a pandemic changed public priorities. In American society, new technologies have repeatedly caused panic about privacy and a sense that privacy is disappearing (Igo, 2018; John & Peters, 2017). I show that there is consistency in the concept of privacy despite societal change. I also show other-regarding tendencies are a factor of the privacy preferences people hold, above and beyond their own beliefs and technological context. This contributes a sociological perspective that foregrounds the way groups of *people* define and enact privacy. In doing so, this dissertation demonstrates that understanding the social processes underlying how privacy is defined and enacted is essential to understand privacy.

By taking a macro approach to studying the meaning of privacy in discourse, I showed that technology is discussed more transactionally than other domains of privacy (i.e. social relationships, legislation). I also show that the terms used to discuss other domains of privacy are quite stable over time, suggesting that established understandings of privacy are not readily changed. This finding contributes a broader perspective to studies of how technology affects privacy. Developments in digital technology, mobile technology, and sensors enable novel capacities to observe and intervene in the lives of people. This finding adds that foregrounding the role of markets and transactions is a novel way of discussing privacy, and so understanding how privacy is recast as part of commerce may be just as important as understanding technological change. It also cautions against equating technological privacy with privacy in general. Even as technology and social life are intertwined, people can sustain different ideas of privacy that may be affected by technology to different extents.

Applying a macro approach to study privacy is also a contribution. Studies of privacy typically focus on sub-groups and types of privacy. Such work is essential to understand the intricacies of how privacy differs across relationships, contexts, and periods. However, this macro approach demonstrates that taking a broad view can both situate cases of privacy within the larger concept, and identify novel changes in the concept for theory building.

I also considered how relational thinking affects privacy judgments during a period of rapid social change. Given that privacy is not simply a personal preference, but is co-created through social relationships, I expected social heuristics would affect the judgments people made about their own privacy. I expected this to be especially true in a period of rapid social change, where privacy and data are more uncertain.

I found prosocial relationship-centered messages resulted in respondents supporting increased surveillance. I also saw weak evidence that discussing disease spread increased support for increased surveillance as well. This suggests public health messaging may have a spillover effect on privacy preferences. It also suggests that people accept less privacy in part for the perceived benefit to others.

However, this finding does not explain whether this effect is caused by changes to a person’s own perception of risk and benefit, or if it is caused by tendencies to defer to others. To consider this question, I explored whether respondents’ privacy preferences were better predicted by their own perception of risk, or the messages about risk they received from other people. I found both affected their likelihood to support increased surveillance, though the effect of the social signal varied by how much a respondent tends to conform to others in general. This finding suggests that privacy behavior is, in part, socially motivated.

These findings lend support for concepts of privacy that emphasize relationships among people (e.g. Marwick & boyd, 2014). It is not obvious what is most important to ensure privacy — for example, keeping information within its context or safeguarding especially sensitive information. This work reinforces that the norms people co-create as they respond to their social environment affect privacy preferences beyond situational factors. Though it is less straightforward, this means privacy interventions must account for the kinds of relationships and expectations in populations they are designed to help. This also implies that models of privacy that focus strictly on individual factors may miss how interaction and social environment manifest in privacy behavior.

This work also presents privacy as a public health behavior. Privacy played an important role in public health long before the Covid-19 pandemic. As public and private institutions are increasingly moving toward applying modern technologies to public health, understanding whether that technology will be accepted and used by the populations it is intended for becomes an important question. These studies also show that the factors that best predict privacy behavior are different from those most predictive of better-studied public health behaviors (e.g. vaccination). This means selection into surveillance programs is likely to vary across social groups. It also suggests groups that require the most intervention to share information with public health authorities may be different from those that require the most intervention to adopt other behaviors.

This dissertation sought to understand whether the meaning of privacy changes as the capacity of technology expands, and whether social relationships continue to play a role in privacy. These questions are informative beyond privacy theory.

First, privacy is an interesting case for economic sociology. Privacy has historically been thought of as something sacred that must be protected because of its purity. Yet the business model of many digital platforms relies on the commercialization of data. This apparent contradiction means digital privacy can be explored from the perspective of a taboo exchange, and both structural (Rossman, 2014) and rhetorical (Zelizer, 2000; Quinn, 2008) explanations may account for when people are willing to accept such markets. Understanding the factors that lead people to accept and participate in markets of data is then an important puzzle (Kiviat, 2019, 2021).

Privacy is also a useful case for sociologically-minded studies about judgment and decision making. Sharing information may have material benefits, but also social risk. This dissertation shows that people may consider both material and social outcomes in their decision making. Further studies of privacy may help to explain how people weigh potential social and material outcomes in their decision making, and also better-explain the processes by which people agree or disagree with others in their environment. This research also cautions against overly-rational interpretations of social heuristics. The case of privacy shows people may conform to others' expectations because it is socially beneficial as much as they may think it's the best thing to do.

In summary, this dissertation considered the meaning of privacy over both a long period and a short but impactful period. It shows social processes, from discourse to social heuristics, affect what people understand privacy to be. Even as the world changes, established notions of privacy have some stability. However, the introduction of new contexts or circumstances can create different privacy norms. By highlighting the social processes underlying privacy, this dissertation serves as a reminder that the social power to define privacy and co-create expectations are important mechanisms underlying lived experiences of privacy. A sociological perspective will continue to be vital to studies of privacy, because both the concept and the material circumstances of privacy are defined through interpersonal and group-level processes.

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