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Technology Support for Online Science Communication

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Abstract

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As researchers, we have an obligation to share our scholarship and act as advocates for scientific knowledge. Participatory platforms like social media have become an important way for researchers to connect with the public, but the shifting affordances, audiences, and roles on these platforms make such public engagement difficult. In my dissertation work, I make three primary contributions. First, I contribute the results of qualitative and quantitative studies to understand how the structure of social media platforms affects the flow of scientific information. Second, empirical knowledge showing that an analytics tool to help researchers understand their audiences better can motivate them to improve the framing of their work, and to make more informed decisions about how (and whether) to use Twitter. Third, methods of communicating large-scale, metascientific information to skeptical audiences online, an issue of pressing concern highlighted by the COVID-19 pandemic. Finally, I discuss future directions for researchers, designers, and policymakers in this space. Ultimately, I show how understanding the dynamics of online platforms can lead to better technology support for various stakeholders in the science communication process.

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Chapter 1

Introduction

1.1 The Problem

You have a problem. Maybe you live in a rural area, an hour's drive from a doctor's office. You start to feel sick; coughing, mucus, a sore throat. You remember the advice you have heard over the years: take ginger ale, orange juice, cranberry juice, vitamin C, zinc, antioxidants, take a hot shower, get some sun, rest, exercise, sweat it out... You wonder whether any of this really helps, and how, and why? It is probably just a cold, but maybe you can feel better without that hour's drive.

Maybe you are a new parent. Housing is not cheap. You found a place you can afford near a major highway, but what about all that fuel exhaust from the cars passing by? What will that do to you? What will that do to your kid? What about the noise? What would it mean for a child to grow up there? Should you pick a smaller place with cleaner air? What is the tradeoff here?

Maybe you are founding a start-up. You think you have a solid idea for a new social media platform, but it will be a big investment. You need to be sure. For now, you need to understand how to compete with existing social media giants. To do that, you need to know their weaknesses. What are their users' privacy concerns? How do their recommender algorithms work, and are they effective, and why? If you build a feature, what will its effect be?

Maybe you are struggling with a health decision, or building a curriculum, or dieting, or voting. Maybe you are a teacher, a lawyer, a physician, a software developer, a nurse, a designer, a poet, a musician, a novelist, a legislator, a researcher, or a community organizer. No matter who you are, you have a problem. You have a question.

In many cases, that question has a scientific answer.

Take multivitamins, for example. Multivitamins are a \$12 billion per year industry, with fully half of all American adults taking some kind of vitamin or mineral supplement (Johns Hopkins

Medicine, 2023). You might naturally wonder, are they worth the \$12 billion expense? Are they good for me? Will I live longer if I take them? The answer to this last question, at least for a typical American without any specific vitamin deficiencies, appears to be “probably not,” according to a summary of research on the subject (Macpherson, et al, 2013). Yet, people still take them. Yes, there are many people with specific health needs which require vitamin supplementation, but for someone who just wants to boost their health? There are better (and cheaper) ways (like eating a healthier diet, exercising...).

While conducting the research this dissertation is built on, I have spoken with dozens (and surveyed thousands) of people with different jobs, different perspectives, different sets of expertise, and different questions. Some may spend dozens of hours sourcing information, tracking down articles and assessing their credibility, to answer just one question. Others may consume more passively, soaking information and building a library of facts, ideas, and perspectives. Some may look to individual scientific experts, government bodies, or popular publications for the latest news. Others may distrust those channels, falling into alternative sources and following the winding paths of conspiracy. Their needs vary, their backgrounds vary, their beliefs vary, their expertise varies, and the sources they use vary.

The one thing that does not vary, however, is that everyone has a need, challenge, problem, or question. My goal with this dissertation is to help ensure our scientific institutions can meet those needs, by building bridges between research and the many publics who seek to learn, engage with, understand, and inform it. In particular, I seek to understand and improve the participatory web (social media and other networks online) as a pathway for science communication. For the rest of this introduction, I will discuss why this is important, and how I have attempted to do so.

1.2 Our Responsibility to Communicate our Research

Very few people are going to read your CHI paper, but you probably have something to say that's relevant to the wider world. Otherwise, why are we even doing this work, right?

The above quote, from a human-computer interaction (HCI) researcher we interviewed during our study on science communication on the participatory web, encapsulates the core motivation for my dissertation work. As researchers, we have an ethical obligation to share publicly-funded scholarship (Zhu and Purdam, 2017) and act as advocates for scientific knowledge (Brüggemann, et al, 2020). To do that, we need to understand how the rapidly-shifting landscape of online media affects the flow of scientific knowledge (Dunwoody, 2014), how to support researchers navigate their evolving roles as advocates and participants in public discourse (Koivumäki, et al, 2020), and how to empower people to navigate a growing deluge of research publications (for example, on the COVID-19 pandemic; do Nascimento, et al, 2021). This is especially crucial in today's context of reduced public trust in science (Kennedy, et al, 2022), a situation linked to heightened conspiracy beliefs and vaccine hesitancy (Wheelock and Ives, 2022). In my dissertation, I seek to better understand how the affordances of social media affect the flow of scientific information, in order to better connect researchers and public stakeholders, improve public access to scientific knowledge, and facilitate increased awareness, understanding, and trust of science.

1.3 What is science communication?

Formally, science communication refers to the communication of scientific knowledge from researchers to various stakeholders, including other researchers, policymakers, journalists and other mediators, and other members of the interested public (Burns, et al, 2003). Science communication can take almost any form, including television (Reid, 2021), radio (Merzagora, 2004), museums (Bell, 2008), magazines (Funk, 2017), news articles (Schäfer, 2017), or even poetry and tabletop games (Illingworth, 2020), wearable technology (Biggs & Desjardins, 2020), public installations (Dema, et al, 2020), and more.

The goals of science communication are multifold, and include increasing the public's awareness, enjoyment, interest, opinion, and understanding (AEIOU) of science (Burns, et al, 2003). Such communication has numerous public benefits, including teaching domain non-experts about scientific topics (Burns, et al, 2013), inviting the public into conversations around scientific issues and influencing scientific agendas, (Trench, 2008), and empowering

non-researchers to engage more deeply with scientific topics (Powell & Kleinman, 2008), all of which play a role in shaping public discourse and debate (de Bruin & Bostrom, 2013). There is clear value in fostering productive dissemination of—and dialogue around—scientific topics in the public sphere.

However, with social media and other online platforms gaining massive popularity in the last two decades, the way the public engages with scientific knowledge has changed dramatically (Dunwoody, 2014). This has provided new avenues for individual researchers to engage with the public (Nisbet & Scheufele, 2009). Using platforms like Twitter (Zhu & Purdam, 2017), Reddit (Jones, et al, 2019), Facebook (McClain, 2017), and YouTube (Welbourne & Grant, 2016), to talk about science in an engaging way (Barel-Ben David, et al, 2020). However, while these new avenues provide promising opportunities for science communication, they have also thrust researchers into uncertain roles (Brüggemann, et al, 2020), and it is not always clear how to leverage this new technology to achieve the AEIOU outcomes outlined above (Koivumäki, et al, 2020).

1.4 Goals and contributions of this dissertation

Ultimately, the goal of this dissertation is to explore how to facilitate science communication online. I do this by conducting five overarching studies (Chapters 3-7), which examine the issue from multiple perspectives. Studies 1 and 3 examine the roles of *researchers* on the participatory web, understanding their motivations and challenges, as well as exploring the design of tools to alleviate those challenges. Studies 2, 4, and 5 focus more on the needs of the *audiences*, those who seek scientific information on the participatory web, and how to improve access, trust, and utility of that information.

My dissertation also explores these questions as they relate to different research domains. Studies 1 and 3 focus on human-computer interaction (HCI), Study 2 focuses on health-related topics, Study 4 focuses on vaccine safety, and Study 5 examines GMO food safety, multivitamins, and mental health. Given the relative lack of science communication research outside of ecology and medicine (Gerber, et al, 2020), this examination of multiple different research areas will help tease apart the domain-specific challenges and considerations that apply to each.

Overall, through this dissertation, I use experiments, interviews, research-through-design, co-design, and social network analysis methods to deepen our understanding of science communication on participatory web platforms, designing new tools and approaches to support that work. I argue that communicating our research is a crucial, ethical obligation, and I hope that by doing this work, I can improve the positive impact that researchers across fields can make on the world.

1.5 How to read this dissertation

1.5.1 Read the whole thing

If you are a member of my reading committee (or, if I am lucky, considering this document for some kind of award), I hope you read the entire dissertation, back to front. Otherwise, you might choose to do so if you are a PhD student yourself who wants an example of how to write a dissertation in this or a related discipline (although there are probably many better examples out there). If you are considering doing a PhD, maybe this will give you a sense of what the work required might look like (although there are countless books, articles, blog posts, and videos to consult if this is your goal).

1.5.2 Read the background and discussion only

If you are interested in science communication (especially how it works online), Chapter 2 (background, related work, and theory) can work as either a brief introduction to some major concepts, or an annotated reading list. It is somewhat particular to my specific research questions, but I have tried to include many foundational works or interesting resources.

Chapter 8 (discussion) starts by summarizing how the research projects in my dissertation (Chapters 3-7) support my thesis statement, and then breaks down their implications for researchers, designers, and policymakers (primarily policy that affects academia and the research world more broadly). If you fall into one of those groups, you can certainly skip to the appropriate section, or read this chapter in its entirety.

1.5.3 Read the research chapters only

If you are interested in reading specific research projects that interest you, I would recommend *not* doing this, since these chapters typically have published papers associated with them that function better as standalone pieces (and none of them are paywalled as of the time of writing). These chapters are of course framed with the broader implications of my dissertation in mind, but if you care about that you should probably just read the whole thing. If you want to learn about these projects in a more public-facing, digestible format, you can also find blog posts about them on my website.

1.5.4 Read the bibliography

Finally, the bibliography of this dissertation is quite extensive, so if you happen to be looking for research in this space, there is a fair chance you can find something relevant there.

Chapter 2

Background, Related Work, and Theory

2.1 Definitions

Before moving into the background and significance of this work, I will formally lay out a few important definitions that will appear throughout this dissertation.

Science communication: I use Burns, et al's (2003) definition: "Science communication (SciCom) may be defined as the use of appropriate skills, media, activities, and dialogue to produce one or more of the following personal responses to science (the vowel analogy)

- Awareness, including familiarity with new aspects of science
- Enjoyment or other affective responses, e.g. appreciating science as entertainment or art
- Interest, as evidenced by voluntary involvement with science or its communication
- Opinions, the forming, reforming, or confirming of science-related attitudes
- Understanding of science, its content, processes, and social factors

Science communication may involve science practitioners, mediators, and other members of the general public, either peer-to-peer or between groups."

Participatory Web: I use Blank and Reisdorf's (2012) definition of the participatory web ("Web 2.0"): "Using the Internet to provide platforms through which network effects can emerge."

Here, "network effects" refer to the phenomenon of something becoming more valuable as more people participate, and a network of people grows. "Platforms" are environments where users can reliably engage in some kind of activity, typically involving user-generated data (videos, blogs, reviews, pictures...). Thus, the participatory web refers to the ecosystem of platforms that empower users to generate content, and includes social media, blogs, podcasts, review sites, etc.

Social Media: While many definitions of "social media" have been used in the past 20+ years, often overlapping heavily with definitions of the participatory web itself (Aichner, et al, 2021), I use Kietzmann, et al's (2011) definition given both its flexibility, and distinction from other strands of the participatory web (e.g. blogs and podcasts): "Social media is a honeycomb of seven functional building blocks: identity, conversations, sharing, presence, relationships, reputation, and groups." In this sense, sites like Facebook, Twitter, Instagram, TikTok, Reddit,

and Snapchat that allow for persistent identities and reputation, group membership, and the ability to communicate and share with each other, would fall into the umbrella of “social media.”

Stakeholders: I use “stakeholders” to mean anyone with an interest in (or who will be affected by) a given topic of scientific study. For example, stakeholders relevant to a study on depression and teen social media use might include teenagers who use social media, their parents, designers of social media platforms, policymakers, etc.

Domain non-experts: This includes anyone who has no more than passing knowledge in a given topic. As per Burns, et al (2003), domain non-experts may have expertise in one scientific topic (e.g. physics) but not another (e.g. psychology or economics). In this way, an individual’s “role” as an audience for science communication is highly context-dependent.

Publics: Rather than speaking about the “general public” as a monolith, I use “publics” to refer to broad, overlapping segments of the population that may react to or engage with science in similar ways. As per Einsiedel (2007), I consider both the public as passive, ignorant observers and as active, critical agents to be oversimplifications, and note that different publics in different contexts may play more active or passive roles in engaging with scientific knowledge.

Science: Science communication research has primarily focused on “science” as a monolith, rather than breaking it down into specific disciplines (Gerber, 2020). While for the sake of simplicity and consistency with science communication as an established discipline I refer to “science” as an umbrella term for all scholarship that advances human knowledge, including the natural, social, and formal sciences (Cohen, 2021), I acknowledge that flattening scholarship into “science” as an umbrella term risks ignoring the unique challenges and considerations of various disciplines, including the humanities (see e.g. Dunbo, 2019).

2.2 Background

2.2.1 The Public’s Perception of Science

In the United States, science has generally enjoyed a high level of trust by the public, with most respondents in a recent Pew survey trusting scientists to act in the public interest, even as trust in

other public institutions falls (Funk, 2020). Trust of science is also quite high globally, particularly in wealthier countries (Sturgis, et al, 2021). However, Americans' trust of scientists has declined since the COVID-19 pandemic (Kennedy, et al, 2022). This distrust—as well as a lack of scientific literacy—can have serious consequences; during the pandemic, a widespread skepticism of Covid vaccines (Wheeler, et al, 2022) led to a sharp rise in preventable infections, hospitalizations, and death (Cuadros, et al, 2022).

Many (35%) Americans believe that scientists can twist the scientific method to produce “any result [they] want,” and trust in science often splits down partisan lines, with far more Democrats than Republicans trusting scientists to make good policy decisions (Funk, 2020). 18% of Americans still denied anthropogenic climate change in a recent survey (Milman, 2019). Genetically modified organisms (GMOs) are another area where public opinion differs from scientific consensus, with as many as 49% of Americans saying that GMO foods are less healthy than non-modified counterparts (Funk, 2018). Perhaps most salient today, public trust of vaccines in the US has become an important concern; Immediately prior to COVID-19 vaccines being made available in the United States, only 61% said they would likely get one (Elflein, 2021), and even a year after vaccines had been made publicly available, only 65% of the country had been fully vaccinated (Our World in Data, 2022).

While these seem to be “mixed messages,” there appears to be a “soft positive” public perception of scientific credibility in the United States (Funk, 2017). While scientists are often seen as authoritative sources on most matters, trust may suffer on topics considered more controversial. Motivated reasoning can play a large role here, as Sharon Dunwoody describes (Cross, 2021):

People are quite capable of viewing scientists as lousy experts when it comes to specific issues that don't fit their notions of what's true.

2.2.2 *Science Journalism*

How, then, does the public learn about scientific topics? Historically, science journalism has (and continues to be) an important means by which the public learns about scientific topics (Brossard & Scheufele, 2013; Dunwoody, 2014). Science journalism has a long history, with large science

news publications (e.g. *Scientific American*) beginning to appear during the late 1800s. During that era, it was common for scientists to write for such publications throughout their career, taking an active role in science communication (Dunwoody, 2014). However, this did not last. As Dunwoody describes:

The beginning of the 20th century saw increasing specialisation in science, which left scientists little time to engage in popularisation. Exacerbating the trend was the growing professionalisation of science, which pushed scientists to see themselves as individuals more skilled than, and apart from, everyday people. As scientists developed their own languages, their own training regimens and their own reward systems, communication with ‘others’ became a low priority.

The above gestures toward the Carl Sagan effect, where even now researchers’ reputations may suffer if they become known as “popularizers” rather than serious scientists (Martinez-Conde, 2016).

In general, specialist science news reporters make up only a small fraction of all news reporting (Dunwoody, 2014), making up no more than 2% of all journalists in various countries across North America and Europe (Schäfer, 2011). Moreover, with traditional journalistic outlets facing increasing economic pressure with the rise of online media, many publications have cut their science news reporting, being more expensive and time-consuming to produce than other news stories (Schäfer, 2017). As a result, science news has been pushed from its already-niche role in traditional newspapers onto social media and other online spaces, in order to maintain visibility and relevance (Dunwoody, 2014). Because of this, the affordances of these web-based platforms now play an important role in how science news articles are engaged with and perceived, ultimately affecting the public’s relationship with scientific knowledge (Brossard, 2013).

2.2.3 *Science Communication on the Participatory Web*

Of course, researchers themselves also share in the responsibility of science communication, and such direct engagement is not a new phenomenon, as mentioned above; researchers have deliberately engaged in public-facing discourse for centuries. For example, Grundmann and

Cavaillé (2000) argue that Descartes consciously addresses two distinct publics in his *Discourse on Methods*: the “learned public,” constituting researchers and other domain experts, and the “curious,” a much larger group with broad interest in the sciences (note that these roughly translate to Burns, et al’s (2003) “attentive” and “interested” publics).

That said, it is now easier than ever for researchers to reach out to the broader public. The participatory web (or Web 2.0), refers to the ecosystem of websites, social media, blogs, podcasts, video-sharing sites, and so on, whose structure centers the user as a content-creator rather than a mere consumer (Blank & Reisdorf, 2012). This has opened up new opportunities for science communication (Nisbet, et al, 2009; Brüggemann, et al, 2020), allowing individual researchers to engage with wide audiences without the oversight of traditional gatekeepers such as journalists. In many cases, researchers can reach audiences comparable to similar, corporate-sponsored media (Welbourne & Grant, 2016), and produce blogs and articles at least as effective as science journalists (Barel-Ben David, 2020). Online science communication and public scholarship also has positive effects on one’s citation count, presumably by improving awareness of their work (Lamb, et al, 2018; Luc, et al, 2020).

However, effective science communication via participatory web platforms is not as simple as tweeting about a paper. A few challenges researchers face when engaging with the public on these platforms:

- Public engagement with researchers’ tweets is often poor or nonexistent (Didegah, et al, 2018), and many researchers are not followed by outgroup members of the public at all (Côté & Darling, 2018). Policymakers are also a difficult audience to reach (Jünger & Fähnrich, 2020).
- Explaining complex ideas to domain non-experts is difficult (Mehlenbacher, 2017), and not all researchers have the expertise to do so.
- Misinformation about research can spread rapidly on social media (Cook, et al, 2018).
- Although researchers have moved into more discursive and less traditional rhetorical practices on social media (Koivumäki, et al, 2020; Mendel & Riesch, 2017), these practices are at-odds with the perception of scientists as neutral and disinterested

observers, which may lead to backlash and loss of credibility (Yuan, et al, 2019; Yuan & Lu, 2020), confusing the path forward for scholars in the public eye.

- In contrast, expressions of personal identity and humor may be necessary in navigating the “collapsed publics” on sites like Twitter and avoiding backlash and harassment (Stewart 2016), further complicating the issue of self-presentation for scientists on social media.

These challenges speak to a need for improved support for those researchers who do want to engage with the public.

2.2.4 State of Science Communication Research

A recent review by Gerber, et al (2020) examines the recent history and current state of science communication research worldwide. The authors make several suggestions for science communication research, including more longitudinal and experimental studies, deeper breakdowns of specific stakeholder groups rather than just the “general public,” more focus on translation between scholarship and practice, examination of fields beyond ecology and biology, more interdisciplinary work to establish deeper theoretical foundations, more large-scale analysis using data mining tools, more systems-focused analyses, more cross-cultural research, more focus on science communicators themselves, and more explorations into rapidly evolving media ecosystems. Accordingly, some have argued for a greater focus on specific communities in science communication research (Orthia, et al, 2021), for research informed by theories of cultural evolution (Bendixen, 2020), and more systemic research on the efficacy of science communication (Kappel & Holmen, 2019). A later chapter in my dissertation will examine how HCI is well-positioned to help address these evolving research directions.

2.3 Theory

2.3.1 Engagement Model of Science Communication

Over the past two decades, science communication research has ostensibly shifted from an emphasis on "deficit models," whereby communication is conceptualized as a one-way flow from expert scientists to an ignorant public, to "engagement models" that emphasize a two-way

flow between researchers and relevant stakeholders (Bubela, et al, 2009). While this narrative of a grand shift from one-way to two-way models has been considered too clean by some, ignoring the persistence (and potential usefulness) of one-, two-, and three-way models of science communication (Trench, 2008), the positive effects of direct engagement with the public are well-documented and include empowering people to participate in scientific issues (Powell & Lee Kleinman, 2008), sparking conversations about research (Besley, et al, 2008), and drawing in the public to help set meaningful research agendas (Trench, 2008). The present work is guided primarily by Trench's notion of "Dialogue" and "Participation" models (Trench, 2008), whereby science communication can be considered both as a two-way conversation between researchers and relevant stakeholders in the public who provide their views and needs ("Dialogue"), or a multi-way flow that includes diverse groups in the conversation and considers how both researchers and other members of the public shape our understanding of relevant scientific issues ("Participation").

2.3.2 *Framing Theory*

Originally put forward by Goffman in his 1974 book, "Frame Analysis" is based on understanding how different actions, messages, or signals are interpreted based on the context surrounding them. As Goffman describes it, someone pointing a gun in your direction carries a very different meaning when that person is an actor on stage at a theater during a period of time bracketed for performance, versus when that person is a stranger in a dark alley at night. That is, the *frame* dictates what is being communicated by otherwise identical actions. Changing frames can involve processes like *keying* (signals that transform the meaning of actions, e.g. slapping someone on the back after a game vs. during a fight), *fabrication* (framing a situation to deceive others), or even *retransformation* (either when activities revert to their original forms, such as a play fight to a real fight, or evolve into a new frame entirely). In short, Goffman's frame analysis is a highly general framework that explains how we derive meaning from the nested frames surrounding our actions and messages.

However, over the next several decades, as frame analysis was taken up by scholars across communication and related fields, the problem of defining what exactly counts as a "frame" became clear (Entman, 1993; DeVreese, 2005). Entman described how frames were often "defined casually" in studies, and DeVreese further noted how studies which deploy frames often

share only a surface-level understanding of what a frame is, suggesting that by defining frames in a haphazard way, studies can claim virtually anything counts as a “frame,” allowing them to purport whatever they want. Ultimately, DeVreese supports Entman’s definition of frames as involving *selection* and *salience*, whereby they define the important aspects of a message in order to define problems, diagnose causes, make moral judgements, or suggest remedies. Furthermore, within the news, Cappella and Jamieson (1997) suggest that for something to count as a frame within a research context, it must:

- Have identifiable language and conceptual features
- Be regularly used by journalists
- Be easily distinguishable from other frames
- Be recognized by people other than the researchers

The communication of scientific research has largely been examined through either a rhetorical tradition (Ceccarelli, 2019) or a scientific one (Gerber, 2020), both of which have demonstrated the utility of frame analysis as defined by the above scholars. Within rhetoric, frame analysis has been used to explain how uncertainty is deployed when communicating about water resource management (Guillaume, 2017), how environmental activism have been overshadowed by the “industrial apocalyptic” rhetoric of countermovements (Peeples, 2014), and how corporations like ExxonMobile use “greenwashed” frames to discourage criticism and critical examination of their anti-environmental actions (Plec and Pettenger, 2012), to name just a few examples. Within rhetoric, frame analysis has led to profound insights both into how scientists communicate about their own research, as well as how other actors deploy science communication for their own needs.

In terms of the science of science communication, significant work has been done to understand how various strategic frames can affect audience attitudes toward issues like nanotechnology (Cobb, 2005), vaccination (Pența and Băban, 2018), and climate change (Bolsen and Shapiro, 2018). Although certain frames from this literature have been shown to resonate with certain audiences and under certain circumstances, inconsistent general effects suggest that numerous mediators and other situational factors come into play (Pența and Băban, 2018; Bolsen and Shapiro, 2018), with frames that might play well with one audience having null or even opposing

effects with others. Bubela, et al (2009) go so far as to suggest that “framing is an unavoidable reality of the science communication process,” with lay publics using them to interpret complex issues, journalists using them to hone in on specific topics and incite interest, policy-makers using them to set the stakes of an issue and persuade other stakeholders, and scientists using them to convince others of the relevance of their findings.

2.3.3 *Psychological Reactance*

Originally put forward by Brehm, et al (1966), reactance theory supposes that when something is perceived as limiting one’s choice or removing one’s freedom, that individual will experience reactance, essentially a motivation to restore that choice or freedom. For example, if someone perceives an anti-smoking PSA as telling them they cannot or should not smoke, they may buy a pack of cigarettes to reaffirm their sense of freedom.

Rosenberg and Siegel (2018) outline 50 years of reactance research in a recent review. In general, reactance theory has been shown to usefully predict people’s response to a variety of messages (including in the climate change domain; see e.g. Chinn & Hart, 2021). While this can be a huge barrier to campaigns aimed at promoting scientific knowledge and prosocial behavior, Rosenberg and Siegel (2018) note that there are a number of interventions that have been shown to reduce reactance. These include:

- Restoration postscripts (i.e., a message that acknowledges the freedom threat they may have experienced, and assures them that they are free to make their own decisions; Bessarabova, et al, 2013)
- Message novelty (distracting from controlling aspects of message; Quick, 2013)
- Narrative (by decreasing perception of persuasive intent, and identifying more with characters; Moyer-Gusé and Nabi, 2010)
- Empathy (e.g. toward characters in a PSA; Shen, 2010; Shen, 2011)
- Inoculation (e.g. warning of an incoming freedom threat; Richards & Banus, 2015)
- Self-affirmation (to put people in positive states, thereby increasing openness to new ideas; Schüz, et al, 2013).

- Framing messages to prompt reactance toward a negative target (e.g. messages that imply smoking reduces one's freedom, and quitting increases one's freedom; Rosenberg & Siegel, 2018)

I draw on some of these concepts in my dissertation work, particularly when exploring how to communicate politically charged concepts (i.e. vaccine safety research) to hesitant audiences.

2.3.4 Uses and Gratification Theory

With roots in mass media research from the 1940s, if not earlier, Uses and Gratification Theory (UGT) models media consumers as active agents, who use various media to satisfy particular psychological and social needs (Ruggiero, 2000). While sometimes criticized for individual studies without strong theoretical throughlines, UGT's focus on audience needs provides a powerful lens through which to view emerging media technologies of the 21st century (Ruggiero, 2000). Reviewing the UGT literature on news audience, O'Brien, et al (2013) identify five primary motivations for reading the news:

- Entertainment (e.g. relaxation, escape, fun)
- Habit (reading news as part of one's daily routine)
- Personal identity (e.g. learning more about oneself, reinforcing one's existing beliefs)
- Social utility (e.g. finding topics of conversation, signaling attributes about oneself)
- Surveillance (seeking information about different topics)

O'Brien, et al (2013) show that these factors are important motivators for online news readers in social context, and I draw on these in my dissertation work exploring science news engagement on social media.

2.4 Research Questions and Thesis Statement

In order to better understand the flow of scientific information through participatory web platforms, and support researchers who engage with the public through these platforms, I will examine three distinct-but-related questions in my dissertation. First, given the rising importance of social media in science communication:

RQ1: How do the affordances of participatory web technologies affect the way science information is conducted, perceived, and engaged with?

Next, with the new avenues individual researchers have for public engagement, and the shifting roles they need to navigate:

RQ2: How can we design tools to support science communication and public scholarship by researchers on the participatory web?

Finally, because recent events (e.g. the COVID-19 pandemic) have starkly illustrated the need for greater trust and awareness of the state of scientific research, my last question explores how we can develop interventions to meet these goals:

RQ3: How can providing meta-scientific summaries of research questions help improve people's awareness of, opinions on, and understanding research on the participatory web?

I answer these questions with five overarching studies (most with their own sub-studies):

- **Study 1** is a set of qualitative interviews with human-computer interaction (HCI) researchers to better understand the strengths and weaknesses of participatory platforms for science communication (RQ1)
- **Study 2** is a set of experiments examining how user-generated comments (a key affordance of social media platforms) affect engagement with science news (RQ1)
- **Study 3** examines how an analytics tool to provide researchers with more insight about their audience on Twitter can affect their science communication practices (RQ2)
- **Study 4** involves the design of “meta-summaries,” which summarize (meta-)scientific information about COVID-19 vaccine safety for skeptical audiences (RQ3).
- **Study 5** explores the link between different types of meta-science information, and specific subdomains of credibility (RQ3).

Ultimately, these five studies support the thesis statement of my dissertation:

“By better understanding the flow of scientific information online (RQ1), designing technology to connect researchers with relevant stakeholders (RQ2) and communicating meta-scientific knowledge to the public (RQ3), we can support online science communication and increase their awareness, engagement, understanding, and trust of science.”

Chapter 3

Study 1: HCI Science Communication on Participatory Web Platforms

3.1 Introduction

To design better systems for online science communication, it was first essential to understand the state of science communication on participatory web platforms: how it is done, how do current platforms facilitate effective communication, and what are the existing barriers? To answer these questions, we (in chapters 3-7, I use “we” to refer to myself and the research team involved in a given study) interviewed human-computer interaction (HCI) researchers about their experiences with science communication on the participatory web. We chose this population for two main reasons.

First, HCI researchers have **expertise in the design of sociotechnical systems**. Given its tradition of longitudinal research of sociotechnical systems (Archambault & Grudin, 2012), focus on social media phenomena (Starbird, et al, 2014), and design of social media features (Jahanbakhsh, et al, 2021), we expected HCI researchers to have keen insights on how the design of participatory web platforms impacts their science communication practices. It has also been argued that HCI is an “inter-discipline,” which responds to the needs and challenges of other fields (Blackwell, 2015). In that spirit, as a field focused on designing, developing, and studying sociotechnical systems, HCI should be well-positioned to investigate and address the challenges of these evolving forms of science communication; so, by focusing on the HCI community, we also hoped to inspire additional research into this space.

Second, HCI (and other computing topics) are **understudied in the science communication space** (Gerber, et al, 2020). HCI is a field that has the potential to spark people's interest in the technology that many of them use every day (Vines, et al, 2013), shape debate about technology (Prost, et al, 2014), and even get designers and practitioners thinking about the unintended consequences of their work (Pillai, et al, 2021). So, while understudied compared to other fields, I argue that it is important to understand and support the direct public outreach that HCI researchers do.

While I want to note that HCI researchers may not share the same challenges that other communities may face in science communication and public scholarship, I think their unique insights---combined with existing research on other fields---can help serve as a foundation for future directions in this space.

This chapter addressed **RQ1**: “How do the affordances of participatory web technologies affect the way science information is perceived and engaged with?” Parts of this chapter have been previously published (Williams, et al, 2022a).

3.2 Related Work: Science Communication in HCI

Some work has been done to investigate science communication and translation issues within HCI itself. Smith, et al (2020, 2022) examine the `Media Production Pipeline", a process which involves both a communication flow through labs, communication departments, and news organizations to the general public, as well as a parallel flow through Web 2.0 platforms like social media, blogs, and organizational websites, noting a number of challenges including a lack of time, competing responsibilities, and difficulty collaborating with journalists. Vines, et al (2013) also examined how HCI research is discussed in the news, and suggests that its easy contextualization into everyday life can lead to HCI research being mis-characterized. Finally, Spaa, et al (2019) looked into how HCI can better engage with policymakers, a key audience for science communication (Burns, 2003).

HCI has also supported science communication around educational, environmental, technological, and health issues. For example, HCI researchers have long advocated for a focus on technology to promote sustainability (Mankoff, et al, 2007), and have indeed devoted growing attention to the challenge of raising awareness of these issues (Ferreira, et al, 2021), developing games (Chan & Leung, 2020) and other artifacts (Biggs & Desjardins, 2020) to support this goal. Vaccines are another important domain of science communication research, and HCI researchers have designed interventions to increase vaccine uptake (Chen & Amresh, 2015) and understand social media users' values with regard to vaccines (Kalimeri, et al, 2019). Other work has examined health communication between patients and physicians (Berry, et al, 2017), as well as in informal settings (Chen, et al, 2013). HCI work has also focused on supporting education

(Sellier & An, 2020), including challenges related to teaching HCI concepts themselves (Oleson, et al, 2020). Finally, the public's reaction to technology-related issues have also been examined (Fiesler & Anninan, 2018), including their perception of online research practices themselves (Fiesler & Proferes, 2018).

The translation of HCI research into design practice may be an issue of particular importance to the community. Colusso, et al (2017, 2019) provide a translational science model for HCI, describing existing gaps between research and practice. Watkins, et al (2020) describes how HCI students carry knowledge between their education and later practice as UX designers, and Velt, et al (2020) propose how different translations can help bridge this gap. As a field, HCI has examined issues of media-researcher collaborations, engagement with policymakers, and the translation of research knowledge into design practice, showing that our community has the interest and capacity to engage with important challenges for science communication.

Finally, despite the shifting roles of researchers on the participatory web (Bruggeman, et al, 2020), and the proliferation of science news on social media in general (Schafer, 2017), relatively little HCI research has focused on how researchers engage with the public directly. Some work has focused on particular online communities like r/science, studying how users share information and discuss scientific topics (Jones, et al, 2019), how technical language can serve as a barrier to entry for the community (August, et al, 2020a), and how user-generated comments can affect users' expectations for and engagement with science news (Williams & Hsieh, 2021). Similarly, other research has explored how moderation and public scholarship is carried out on r/AskHistorians (Gilbert, 2020), and how information seeking practices vary between this subreddit and the \#AskHistorians hashtag on Twitter (Gruzd, et al, 2020). Instagram has also been examined as a means of sharing experiences at natural history museums (Weilenmann, et al, 2013).

However, while these investigations provide insight into how the design of social media platforms affect engagement with science news and artifacts, there is less attention paid to the role of researchers themselves on these platforms. Gero, et al (2021) do explore how researchers on Twitter explain complex topics in ways accessible to the broader public, but there is relatively

little HCI research focused on understanding the challenges facing researchers who engage with the public on the participatory web, and how technology can be designed to support researchers who do this work.

Thus, this work provides an initial, deep look into how researchers approach the participatory web as a site for science communication, and how the designs of those platforms affect their practices in this space.

3.3 Methods

3.3.1 Participants

An initial set of 20 participants were recruited via direct email solicitation to specific former CHI PC members (2016-2018). This group was chosen because CHI is the largest HCI conference and acts as an umbrella venue to smaller conferences, such as CSCW, GROUP, or UIST.

Interviewing program committee members from various subcommittees allowed us to hear from community members that were active HCI researchers who have identified with the community for at least a few years, and who work in various subareas of HCI. Given the relative lack of early-career (i.e. PhD student and postdoctoral) researchers represented in the PC, we conducted a second round of recruitment where we expanded our pool to the students of former PC members from between 2016-2020, who had published at least one paper at CHI. We chose this last criterion to ensure they had published research to discuss online, expecting they would have insight into potential challenges therein, as well as to ensure that they had been active as members of the CHI community. Our final sample totaled 24 researchers.

Potential interviewees were contacted with a request for a 30-60 minute remote interview, via Skype, phone, Zoom, or another tool of their choosing. Participants' demographic data are aggregated to protect anonymity (see Table 1).

Position	Full professor (or equivalent)	1
	Associate professor (or equivalent)	5
	Assistant professor (or equivalent)	8
	Postdoctoral researcher	2
	PhD student	4
	Industry researcher	4
Institution	North America	16
	Europe	3
	Asia	5
Subcommittee	Accessibility and aging	2
	Design	2
	Engineering interactive systems and technologies	4
	Games and play	1
	Health	3
	Interaction beyond the individual	3
	Interaction techniques, devices, and modalities	3
	Learning, education, and family	3
	Specific application area	9
	Understanding people	8
	Visualization	1

Table 1. Aggregate summary of interviewee demographic information.

3.3.2 Interview Protocol

All interviews were conducted remotely by three members of the research team, either solo or in pairs. The first three interviews and one pilot interview were done by all three interviewers to ensure consistency. All interviews were recorded and later transcribed.

The interview protocol was developed collaboratively by the entire research team. First, in order for us to better understand researchers' use of existing tools for science communication, participants were asked to describe what tools they most commonly used, how long they had used each tool, why they used them, whether they accomplished their goals, and what features are currently missing from them. They were also prompted about other areas that may present challenges, such as whether specific audiences were difficult to communicate with, potential challenges in their review process (if they had one), and how they advertise their outreach. We additionally asked about their motivations for doing science communication in general, what they consider their role to be, and how they judge the success of their communication. For the full set of questions, see Appendix A.

Analysis of the interview data was done using a thematic analysis approach (Braun & Clarke, 2012). The first interview was openly coded by four members of the research team, who then met to develop the codebook. Two of us independently coded a subset of the interviews and used that data to develop the final version of the codebook. I subsequently re-coded the entire set of transcripts using the final codebook, which categorized the data into different types of barriers, motivations, strategies, resources, and tools, with 14 high-level codes across these categories. After coding the data, each code was imported into the collaborative application Miro.com, where three authors met to affinity map the data and identify potential themes. The entire research team met twice more to discuss the findings and emergent themes.

In the following, interview quotes are not tied to individual pseudonyms to further preserve anonymity and are lightly edited for readability and clarity (e.g. removing "filler" words, pauses, stutters, etc.). All italicized sections have been added here for emphasis.

3.4 Results

3.4.1 *Researchers' Motivations for Science Communication*

Our sample showed a number of different motivations for communicating their work to various public audiences. A first class of motivations are concerned with **individual benefits and**

self-promotion. Some interview participants suggested that public-facing communication can lead to more citations of their scholarly work:

Even if your blog post isn't going to get 1000 hits from lay people, the audience of academics is also really important because, even if only a subset of academics are going to read your CHI paper, a larger percentage of them might take five minutes to skim a blog post, and then maybe decide to read your paper, and then maybe cite it.

This idea is backed up by relevant literature, which suggests that social media presence positively correlates with increased citations (Lamb, et al, 2018; Luc, et al, 2021)). Another facet of self-promotion includes making connections (i.e. science communication as ``dialogue" rather than one-way ``dissemination;" Trench, 2008). One such group might be prospective students:

One reason for doing press work is to make yourself known to potential students who come here and want to get a PhD, and for that purpose it's kind of pointless to be on just some random paper. Being on the internet is actually where these people are.

By discussing their work via different public mediums, many participants felt they were able to make connections with potential students, participants, and collaborators, focusing on engaging with diverse audiences as well as disseminating information.

Similarly, some participants discussed the idea that public outreach can improve one's **funding opportunities**, particularly when they are picked up by the media:

It turns out that some of the news media articles and so on are quite effective to persuade the funder...I show that this is what we have done, and it's pretty effective...We're giving the impression that we're actually quite serious about promoting the results.

However, self-directed efforts (e.g. blogs, social media) were not considered as effective by one of our participants: "I think anybody who thinks that blog posts are going to give them grants is sorely mistaken." Furthermore, other participants felt like there were no personal incentives to talking to the media, providing a competing perspective to the perceived funding benefits:

I think it's really important that we are talking to the media, not just our academic community, but again, that takes time. Is that rewarded? You know, are faculty incentivized to do that kind of thing? And that's why maybe we all don't.

Past research has noted that public communication can provide some funding opportunities even as it incites backlash from other agencies; this backlash may be due to the perception that heavily popularized researchers are "substandard," or that their work is "overexposed" and therefore not deserving of grant opportunities (Martinez-Conde, 2016). Both our data and past research paint a complex picture of the potential costs and benefits of outreach.

Another class of motivations are based on broader societal benefits: to **increase public interest** in, and trust and understanding of, the scientific process. One participant discussed emphasizing the importance of science:

As a scientist, I have a responsibility for maintaining the respect and the use of people who are doing science, and that one way to do that is to share the things that I do, and that my colleagues and other people do effectively, in a way that shows that utility for people who may not understand.

Others discussed the importance of teaching the public to better evaluate scientific claims:

The thing that I'd most like to communicate is, I'd like to encourage the public not to believe everything they read. So, skills like, how to read a paper, how to make sure that you don't blindly trust scientific findings, how to form your own opinion. I mean, that is something that I've noticed, for example, in the anti-vaccination

debate, that a lot of it is well-intentioned people, who don't really understand the scientific literature or scientific process, and that worries me.

Finally, a common motivation for communicating one's work is to **provide useful knowledge to the public**:

Very few people are going to read your CHI paper, but you probably have something to say that's relevant to the wider world. Otherwise, why are we even doing this work, right?

This sense of responsibility was often directed toward the general public, and this type of outreach was seen as a way of making complex research accessible to a broad audience:

If I can do something to take the complex stuff that we do here in the university world, and present it to somebody in a way that they can understand, if I can write a short article that explains to somebody precisely how [social media topic] works so that they don't have to read really long in depth articles about it...then I'm happy.

Sometimes the intended audience was more specific, with some participants targeting practitioners in various fields such as software engineering, design, and education:

You talk to a software developer who's at Microsoft and has worked there 10, 15 years or whatever, they probably aren't actually reading research papers, they probably aren't reading the ones that have that STS and critical theory, and this is a format that just doesn't work well in their context. So, how can we take all of this interesting work that exists on inclusion in critical theory, things like data violence, and what does inclusion look like in tech that exists? And how do we bring it to people that are actually making this in the moment, they're sitting there, they're coding, and they have a choice to make a design decision that makes a difference in the world.

3.4.2 *Online platforms*

We identified six main themes related to the pros and cons of online platforms for science communication. The first theme showed that social media and blogs are commonly welcomed by researchers as a way of **communicating scientific results without traditional gatekeepers**. For example, one participant, who primarily used Medium blogs to communicate about their work, noted that "...my success rate from actually reaching out to journalists is exactly zero. Like they won't even reply." While several participants said their institutions' media specialists helped open them to traditional media channels, many others did not have access to these resources, communicating mainly through social media and blogs. Participants acknowledged that the increased control that resulted from directly communicating scientific findings themselves also helped them avoid their work being sensationalized

...as academics writing as science journalists, it's sort of within our value system to do that really carefully, right? To not over interpret our results and not ignore prior work...

Similarly, because there is no peer review, researchers had full control over what they wrote online. This provides researchers the freedom to discuss whatever they want, at the potential cost of reducing rigor:

The blessing and the curse of doing this dissemination to the general public, is you can say whatever you want, right? Once you do this kind of add-on component, it doesn't have peer review. It doesn't have to be this rigorous set of strategies that are empirically validated, right?

Another advantage of maintaining a social media account or blog is to serve as an **archive of past communication activity**. Some participants mentioned Tweet threads and blogs as ways of providing a longitudinal record to help reflect on their interests or public behavior over time:

The question of actually being able to save these things or have some collection of them is really interesting to me. At one point I started a blog...and one of the reasons why I wanted to do that was because I can have control over things like archiving...which is really useful if you want to be able to actually have something and refer to it later.

Beyond self-reflection, the idea of archiving one's work for public consumption was also appealing. One participant described using a combination of blogs and Twitter to provide a publicly-accessible repository of their work ("I'll like put everything there in case people are wanting to find it, and then of course like I'll promote them on Twitter.").

In general, although participants used social media platforms like Twitter and Facebook to broadcast their research to a wider audience (echoing the advantages stated in the above section), several interviewees identified limitations to their use for science communication. For instance, there can be a **diverse mix of audiences on social media**, with some researchers struggling to balance the platforms as both personal and professional channels ("It's your family life, it's your work life, it's your academic life. So I have to play all these roles all together, and then the audience is all messed up too"). This may be especially difficult given the constant shifts in how platforms are structured and who uses them:

It keeps changing, the way I perceive Facebook as a channel for communicating my research. I think the dynamics are continuously changing because the audience changes, because how other people use Facebook changes as well, so I think I tend to somewhat adapt to what I think is more appropriate.

Researchers may also **lack metrics and feedback** about who is engaging with their work. While platforms like Medium and Twitter provide certain metrics of engagement, they may not allow for more fine-grained insights about the diverse mix of audiences interested in HCI work:

I would like to know the identities of the people who are reading these things, who is re-tweeting it and know more about them. And in some ways all of that data's just there. It's just not curated in a way that's easy for me to see at a glance.

This uncertainty relates to another point of tension: despite difficulties in knowing who one's audience is, many participants emphasized the importance of understanding their audience to best contextualize and communicate their work. One participant pointed out that this lack of audience visibility can also prevent researchers from receiving useful feedback:

If somebody reads a blog post and replies to me or talks to me about it, I know that they're engaged in that work, but I don't know if somebody didn't read it, I don't know if somebody read it and didn't like it because most people are not going to like email you and say, "this is stupid" or whatever. You don't really know why something didn't succeed.

Thus, using conventional metrics, it may be difficult to incorporate available user engagement data into productive feedback. Some participants suggested that knowing more about the impact, such as through tools that could visualize or summarize how science communication spreads, would be useful:

So maybe that would be like a metric of success. Getting deeper into the community, or seeing people actually take things on or hearing them tell you about what they did or what they're going to think differently. Just being able to visualize the ripple effect.

Another related challenge was that, beyond the need to juggle diverse audience interests, researchers often had difficulty accessing these audiences in the first place, due to a **lack of targeting mechanisms**. For example, when writing blog posts on Medium, some participants were unsure how to target specific audiences ("It shows up, and then it just kinda sits there...There's no targeting you can do past just putting it in a specific bucket of a publication and just hoping people see it").

Another participant echoed this concern around targeting blog posts, discussing possible technological features that may help:

If I could know that a blog post was actually going to be added to like some aggregation service, that journalists actually check, I would be like much more likely to blog and I would put more time into my blogs and I would think about them slightly different. Like I would write more for the general audience.

In some cases, participants mentioned using services such as Slack channels or email lists to target specific groups of academics or industry professionals. However, as other participants noted, reaching the non-expert public may present additional challenges, as they may not be accessible via the same channels that more specialized audiences are, a concern that is somewhat supported by the existence of academic filter bubbles for other fields' Twitter presence (Côté & Darling, 2018).

Finally, while previous research has noted that some researchers turn to Web 2.0 channels to gain greater control of their narratives than they might have working with mainstream media (Smith, et al, 2020), the affordances of platforms like Twitter ("Explaining my [work] takes more than 280 characters") can **make contextualizing one's work difficult**, allowing those narratives to spin out of control and damaging their ability to engage with the public:

[Twitter is] not great for conversation, it's not great for debates. It's certainly good at like generating all kinds of miscommunication, right? You can enter in an argument with somebody and spend like 50 replies trying to clarify what you meant because your original 280 characters wasn't clear enough. So sometimes what I broadcast turns into those things and sometimes that leads to interesting conversations, but oftentimes it's just a whole bunch of really broken communication.

The way conversations are displayed can also make it difficult to track conversations, either leading to misunderstandings or impairing the ability to follow conversations:

Twitter is fine for browsing through these short bursts of comments that could be funny, or has this one interesting idea in it in very short sentences, but I wouldn't really call it an in-depth discussion, per se. You know, sometimes people try to have an in-depth discussion, and I sometimes see good-quality discussion happening, but from the user's point of view, it's really hard to track what exactly is happening, because of the way the thread is visualized and displayed.

3.5 Discussion

With RQ1, I wanted to better understand how the design of participatory web platforms affects science communication online. The results of Study 1 suggests that while researchers can be highly motivated to use platforms like Twitter, Facebook, or Medium to get their work to various publics (to inform, to educate, or to self-promote), the way platforms are currently designed leads to a number of challenges, including uncertain audiences, lack of feedback, and an inability to target the publics who could really make use of one's work. In order to help researchers do this work, those challenges need to be addressed.

To do so, I'll discuss three design directions that follow from these results: audience analytics, outreach incentives, and feedback tools. I will follow up on these directions in Chapter 5.

3.5.1 Audience analytics and framing strategies

One challenge our participants faced was in navigating the mix of audiences on participatory platforms; it wasn't easy to frame their work when dealing with multiple overlapping audiences, especially when they don't know who those audiences are. Moreover, we found that without adequate targeting mechanisms, it can be hard to reach specific audiences when one's work calls for it (e.g. a blog post on web design should reach web designers). Effective science communication relies on knowing one's audience (Cooke, et al, 2017), but given the ever-changing demographics on sites like Facebook (Gramlich, et al, 2019) and Twitter (Oktay, et al, 2014), it can be difficult to determine what the right platform is when trying to reach a

specific audience. To provide better insights on who one is reaching, researchers will need tools that provide an overview of their audience. These tools could use analytics on sites like Twitter to help estimate what broad groups (e.g. researchers, practitioners, domain non-experts) are being reached by any given tweet, post, etc. This could be done by building on the keyword-matching techniques used in previous science communication work, to predict whether a given Twitter user is a researcher or not (Côté & Darling, 2018; Kopke, et al, 2019), or what domains they have expertise in.

However, even knowing who one is reaching may not be enough; researchers must still determine how to frame their work for these audiences. To that end, strategies to automatically identify science communication writing guidelines (August, et al, 2020b) could be leveraged to provide writing suggestions for tweets or other posts. For example, if a tool like this finds that one's Twitter audience is largely domain non-experts, it could also recommend using metaphors or relating one's research to current events, to more effectively engage with that audience. Our participants sometimes found it difficult to reach out about certain contribution types, so providing suggestions based on existing guidelines or others' strategies could help when navigating this issue.

3.5.2 Incentives for promoting outreach

Another significant challenge for our participants was a general discomfort with public outreach, which manifested in three key ways. We found that researchers in our sample are often uncomfortable with self-promotion, due to lack of confidence, fears about coming off as too much of a self-promoter (fears which may not be unfounded based on the persistence of the Carl Sagan Effect; Martinez-Conde, 2016), and gendered expectations of modesty around one's accomplishments (a known challenge for self-branding in other contexts (Lindeman, et al, 2019; Thompson-Whiteside, et al, 2018)). There is a tension here, where the need to self-present as a confident scholar and expert may be incongruous with their backstage personas in online spaces (Hogan, 2010). Researchers found this can be uncomfortable and difficult to navigate.

Because some participants noted that receiving endorsements from others may feel less awkward, providing mechanisms and/or incentives for community members to broadcast each

other's work could help reduce this discomfort. One possibility would be to provide automated dissemination tools whereby researchers could write blog-posts and/or short blurbs about their publications and broadcast them to Twitter, Reddit, etc. While as of the time of writing, the ACM provides free use of the communication service Kudos (Kudos, 2023) to its authors (which provides users with templates to write and generate shareable one-page PDFs about their work), authors must still share the work themselves. An automated system could take this one step further, broadcasting such templates and easing the burden of self-promotion from researchers themselves, perhaps by posting to social media accounts branded by specific conferences or journals.

3.5.3 Tools for providing feedback

A related issue brought up by several participants was a lack of feedback mechanisms, meaning that researchers have a hard time judging what constitutes a successful blog or post. So, future tools or platforms could be designed with consideration for deeper feedback mechanisms. At a high level, this might include aggregating quantitative engagement data to compare with various aspects of one's outreach, such as topic, length, channel, time of day, to reverse-engineer the qualities of a successful post. For more specific feedback, perhaps platforms could encourage more (productive) user commentary, allowing researchers to more clearly see why their science communication succeeded or failed. The current lack of these comments on Twitter may indicate a need to incentivize 'upstream engagement' (Bubela, et al, 2009), whereby non-researchers are drawn into the research process as participants and stakeholders. By signaling that researchers value the perspectives of the broader public, it may be possible to encourage relevant stakeholders to follow, comment on, and discuss with researchers about their work, providing a more direct avenue for dissemination and engagement while simultaneously providing useful feedback for how researchers conduct and frame their work for the public.

3.6 Closing Thoughts

This first study highlighted how the post-normal roles of researchers in participatory web spaces can cause uncertainty for science communication, muddying the waters and making it unclear who one is talking to, how to reach one's intended audience, how to frame one's work, and how to generate feedback to improve as a science communicator. Despite this, researchers clearly see

the value in this work, and I believe the findings and suggestions here can pave a path forward for additional research and design interventions to improve the science communication flow online (see Chapter 5).

Additionally, HCI has proven to be a useful testbed for questions around science communication. While later studies in this dissertation will focus on topics of significant public controversy (e.g. vaccine science), the diversity of stakeholders and audiences that HCI touches (e.g. researchers, designers, software engineers, educators, healthcare providers, lawyers, policy makers...) highlights how important it is to study the needs of those diverse groups, and how to engage with them. Chapter 6 will focus more on the needs of one particular stakeholder group (vaccine-hesitant people in the U.S.), but this is a rich question worth tackling, and I believe future work should be mindful of the huge number of sub-groups that interact—in one way or another—with HCI and other applied fields.

Before moving on to build out some of these tools, or study how to communicate with specific audiences, there is still an important angle to RQ1 that remains unstudied. Perhaps the defining feature of the participatory web is user-generated content, and in particular, the comments that users leave on posts, tweets, and videos. While Study 1 focused on how platform design affects how researchers approach science communication, Study 2 will focus on how it affects the audience.

Chapter 4

Study 2: How User Comments Affect Science News Engagement on Social Media

4.1 Introduction

With the decline of traditional newspapers in the US and beyond, the already-fringe role of science journalists in traditional news outlets has decreased further, pushing them into social media and other online channels in order to remain active and visible to the public (Dunwoody, 2014). This emphasis on social media means that science news now frequently appears in the context of online platforms like Twitter, Facebook, and Reddit, and the affordances of these platforms can affect the way it is engaged with and perceived (Brossard, 2013). In particular, preliminary research has shown that user-generated comments can affect people's risk perception of the technologies discussed in science blogs (Anderson, et al, 2014), and even certain people's agreement of a science article's slant (Winter & Krämer, 2016; Winter, et al, 2017), highlighting their potential importance in the way social media users interact with science news in the modern era.

Past research on the effects of user commentary on news perception has focused on typical blog and online news platform formats; that is, participants would read the text of an article, and then read the comments which follow (Winter, et al, 2015; Winter & Krämer, 2016; Lee & Jang, 2010; Lee & Tandoc, 2017; Anderson, et al, 2014). However, social media platforms like Facebook and Reddit allow users to view comments before following the link to a posted article. In particular, recent research on Reddit's *r/science* sub-community suggested that its users often read user-generated comments before the article itself (Jones, et al, 2019). Because of this, comments may have the potential to signal various qualities of an article before a person even reads it, potentially impacting their likelihood of reading the article at all.

In this chapter, I'll examine how different types of user comments affect readers' perceptions of science articles posted in an *r/science*-like context, as well as their intention to read them at all. This chapter will be broken down into two studies. Study 2a examines both comments' agreement with the article and their difficulty, providing experimental evidence that difficult

comments reduce people's likelihood to read the associated article, regardless of their particular slant. Study 2b is a follow-up experiment that shows that people's expectations for science news articles are affected by a similarity heuristic; the attributes of a comment such as its difficulty, entertainment value, or information quality can signal those attributes of the article itself, impacting their decision to read the article or not. Ultimately, I show how different types of user commentary can impact people's interest in reading science news articles, an important consideration for science communication over the participatory web.

This chapter continues to address **RQ1**: “How do the affordances of participatory web technologies affect the way science information is perceived and engaged with?” Parts of this chapter have been previously published (Williams & Hsieh, 2021).

4.2 Related work and hypotheses

4.2.1 Effects of User Commentary on News Perception

Over the past several years, social media has become an increasingly important source of science news (Schäfer, 2017). The public has recently turned to mixed media for their science news, relying not only on traditional formats such as television and newspapers, but blogs and social media sites like Facebook, Twitter, and Reddit (Su, et al, 2015). One important affordance of such online platforms is the presence of user comments (Lee & Jang, 2010).

While few studies to date have examined the interaction between user commentary and science news perception specifically, a significant body of work over the past decade has shown that user-generated comments in general can impact readers' perceptions of their associated articles in a number of ways (Lee & Tandoc, 2017). For example, negatively-valenced comments have been shown to reduce readers' perceptions of article credibility (Heinbach, et al, 2018; Waddel, 2020) issue importance, relevant behavioral intentions (Spence, et al, 2017; Zeigele, et al, 2018) and the persuasive power of the article itself (Winter, et al, 2015; Winter, et al, 2017}, as well as activate prejudices and affect participants' perception of reality (Lee & Tandoc, 2017). Comments that disagree with the article's message have also been shown to affect certain participants' personal opinions about the associated issue, as well as their inferences about public opinion (Lee & Jang, 2010; Walther, et al, 2010; Houston, et al, 2011).

Beyond the effects of specifically negative comments, others have examined how the quality of reasoning and level of civility in the comments section affects article perceptions. For example, the presence of poorly-reasoned comments has been shown to reduce people's expectations about the informational quality of the associated article (Prochazka, et al, 2018). The same study also showed that the presence of uncivil comments can decrease people's expectations about the "formal" quality (i.e. various factors associated with the quality of writing) of the article, even suggesting that the mere presence of any type of comment may reduce readers' quality expectations. Thus, it is possible that even positive or neutral comments could have a negative impact on people's perceptions of their associated articles.

Notably, the bulk of past research has shown user-generated comments to participants following the article rather than before (Winter, et al, 2015; Winter & Krämer, 2016; Winter, et al, 2017; Anderson, et al, 2014; Lee & Jang, 2010; Lee & Tandoc, 2017; Walther, et al, 2010; Houston, et al, 2010), mirroring the structure of typical online news outlets and blogs. However, while a few recent studies have noted this problem and studied how reading comments *before* an article can impact people's impressions of it (Prochazka, et al, 2018; Waddel, 2020) , these studies do not provide clear mechanisms for how different comment types can affect people's expectations for the article, nor do they investigate how those expectations might ultimately affect people's interest in reading the article itself. Given that social media sites like Facebook, Twitter, and Reddit present comments before users navigate to the posted articles, such effects could have significant implications for how people engage with the news on such sites, but current research on this topic is sparse.

Thus, the primary, overarching research question across both sub-studies in this chapter is concerned with filling in this existing gap in the literature, and understanding how different comments impact people's expectations of, and interest in reading, science news article:

SRQ0: How do different types of user-generated comments affect people's expectations of related science news articles, and how do those expectations affect their interest in reading the articles themselves?

4.2.2 *Science News on Social Media*

Online blogging has become an important source of scientific and educational information for both expert and lay audiences (Head, et al, 2017), and individual researchers often make use of such channels in order to communicate their work to a wider audience (Jarreau & Porter, 2018). Other social media channels, such as Reddit, have also become important avenues for disseminating scientific information (Jones, et al, 2019), and many researchers believe that communicating about their research through these channels can benefit the public overall (Zhu & Purdam, 2017).

In particular, Reddit may be especially relevant to the study of user commentary and science news, specifically with regard to its “sub-reddit” r/science. r/science is a hub for users to post and discuss recent science news, boasting over 22 million registered members (Jones, et al, 2019). Because of the way the site is structured, clicking on the title of a Reddit post immediately brings up the attached comments section, and past research has shown that r/science users often read the comments before the article itself, potentially coloring users’ perception before they navigate to the original source. Given Reddit’s importance as a news source for millions of people worldwide (Ovadia, 2015), this affordance could have significant impact on the way its users selectively engage with the news.

While a wide variety of comment types have been identified on r/science, one that regularly receives a high proportion of “upvotes” (and consequently, more visibility based on Reddit’s algorithm for displaying comments) is the method critique (Jones, et al, 2019); comments that question the methods used in the underlying study may be among the top comments for a given post, and thus the first thing that many users would see after clicking the post title. Because of the numerous effects of negatively valenced comments for general news articles, it is possible that these critical comments may also negatively impact reader’s perceptions of the article’s message, its persuasive power, or the credibility of the underlying science.

Beyond that, such critique may impact how likely a person is to read the associated article at all. In general, people show more interest in a task when they perceive it as having value or utility (Hidi & Renninger, 2006). Furthermore, people have been shown to be more likely to read news

articles when they perceive them as having higher information utility (Kim, et al, 2016). If participants believe that the methods used in a study are suspect, and if they then decide that the study's findings are invalid, they may consequently perceive the article as having low information utility, which would in turn discourage them from reading the article, as there is less apparent worth in doing so. Thus, for Study 2a, I hypothesized...

H1: People who read negative comments will show less interest in reading the associated article.

Of course, the above assumes that people are basing the usefulness of a task on its informational utility. It is possible that, for participants who typically engage with science news for other purposes (e.g. social, entertainment), they may still be interested in reading a paper whose methods have been criticized by others. Given this possibility, I hypothesized an interaction such that participants' motivations for news will impact what effects different user commentary will have:

H2: Participants who are motivated by the informational aspect of reading science news will be less likely to read an article with a negative comment, but that this effect will be weaker for participants who are motivated by factors other than information.

Finally, it is also unclear what effect positive critiques would have on readers' perceptions of the article. While the effects of negative comments are well-documented, previous research has consistently shown that positive comments do not have an equivalent effect (Winter, et al, 2015; Waddel, 2018). However, because positive research method critiques for science news have not yet been studied, it remains to be seen whether reading such opinions will increase people's agreement with the article's findings, or the quality of the underlying research.

SRQ1: What effect, if any, will positive comments have on participants' interest in reading the article?

4.2.3 *Difficulty of Scientific Texts*

Balancing accurate scientific information while avoiding technical jargon is a well-known challenge for science writers (Ecklund, et al, 2012; Sharon & Baram-Tsabari, 2014), and user-generated comments that are difficult to understand may be a barrier to broader accessibility in communities like r/science (Jones, et al, 2019). However, beyond creating a higher barrier to entry for lay audiences, the difficulty of a scientific text has been shown to impact people's judgements about its findings, their confidence in the material (Scharrer, et al, 2012; Schäfer, 2017), and even their interest in and identification with science as a whole (Shulman, et al, 2020). For example, the presence of technical jargon (Schäfer, 2017) and arguments based on empirical evidence (Keil, 2010) may be more difficult for lay audiences to process, making them feel like they do not understand the article.

Thus, one potential effect of reading negative comments would be a decreased interest in reading the article. People who read difficult comments may become less interested in the article's topic, or they may feel like they will not understand the article. Thus, one hypothesis would be...

H3_a: People who read a difficult comment will show less interest in reading the associated article.

However, it is possible that difficult comments may have the opposite effect. Recent research has described an "easiness effect" of science texts, where people who read more difficult articles show less confidence in their understanding of the material, whereas reading easier texts may make them overconfident (Scharrer, et al, 2017). In this case, people who read easier comments may feel like they already understand what the article is trying to say, and consequently feel less need to read it. In contrast, those who read a more difficult comment may have more interest in reading the article, in order to better understand the issue. Thus, as a competing hypothesis to H3_a:

H3_b: People who read a difficult comment will show increased interest in reading the associated article.

In order to examine these hypotheses, we conducted an experimental study to investigate the effects of user-generated comments on people's interest in reading science news articles.

4.3 Study 2a: Comment Valence and Difficulty

Study 2a uses experimental methods to determine the effects of a comments' difficulty and agreement with the associated article on participants' interest in reading that article. By showing participants different versions of an r/science comment that varied along the above dimensions and surveying their intention to read it, we provide an initial exploration into how different types of comments impact people's interest in reading science news articles.

4.3.1 Methods

This study was a between subjects experiment with a 2 (comment's agreement with the article: positive or negative) \times 2 (comment difficulty: easy or hard) + 1 (control) design, for a total of five conditions. Participants were shown a mockup of a reddit post (see Figure 1) that linked to a science news article, as well as one of the possible comments (or no comments in the control condition). In order to isolate the effects of specific comments, our study focused only on a single-comment scenario; however, while many comments sections on Reddit have few or no comments (Woolf, 2014), our results may not fully generalize to posts with many comments.

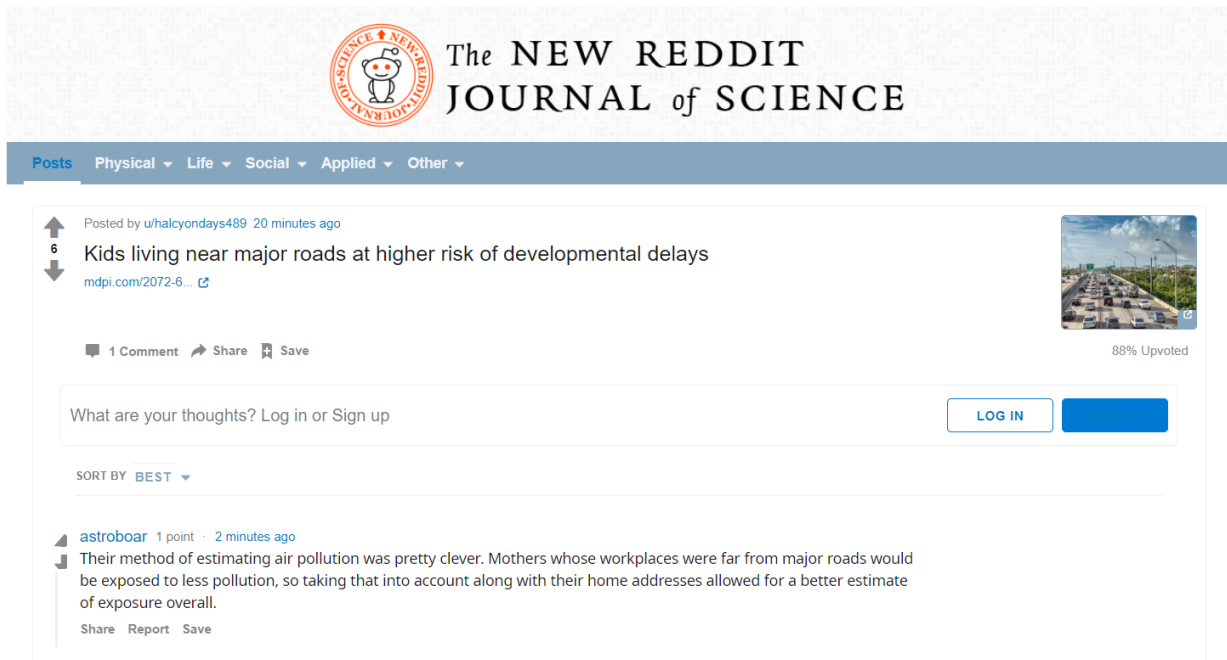


Figure 1. r/science mockup used in Study 2a. User names were generated specifically for this study and were not in-use by any actual Reddit users.

Once participants answered questions about the comment and their likelihood of reading the article, they were then directed to the article itself. The chosen article fit r/science's guidelines for appropriate material based on quality, relevance, and recency from when our study was conducted, and was determined to be representative of a typical r/science article.

Participants. A total of 611 participants were recruited on Amazon Mechanical Turk (AMT). The study was advertised as "Read a science news article and answer a survey." After excluding those participants who failed the attention check, those who reported skipping the comment, those who could not answer what the comment was about, and those who dropped out of the survey partway through, the final sample size was 298 (age: $M = 31.4$, $SD = 8.9$). In terms of gender breakdown, 185 participants identified as male, 111 identified as female, and 2 identified as non-binary. The sample was 46.3% (138) White, 41.9% (125) Asian, 3.7% (11) Hispanic or Latino, 3.0% (9) Black or African American, 1.3% (4) American Indian or Alaska Native, 0.3% (1) Pacific Islander, and 1.0% (3) who chose not to say. 59% (176) of the sample reported using Reddit at least once a day, and 91% (271) reported using it at least once a week. Most (66.78%,

199) either "agreed" or "strongly agreed" that "Reddit is a good source of science news," with only 14.09% (42) who "disagreed" or "strongly disagreed."

Stimuli. The chosen article was a summary of a recent study done on the relationship between living near a major roadway and developmental delays in children. Beyond being chosen for its appropriateness based on r/science's rules, it was also expected to be a topic of relative interest to the general public. The article was 671 words long, and was included within the questionnaire using a single, sans-serif font and with no attached advertisements.

All four comments focused on the authors' method of estimating air pollution in their study, given the high visibility of this type of comment on r/science (Jones, et al, 2019). The positive comments provided an argument for why "the authors' method of estimating air pollution was pretty clever," which focused on their use of workplace location data to better estimate pollution exposure throughout the day. The negative comments provided an argument for why "the authors' method of estimating air pollution was pretty poor," which was based on the lack of traffic data attached to the roadways being studied, which could have provided a more accurate estimate of air quality.

Difficulty was manipulated as per Scharrer, et al (2017). That is, the easy comments contained a direct causal explanation for their arguments, were shorter in length, and contained no complex language, abbreviations, or jargon. On the other hand, the difficult comments provided links to other studies and web pages to back up their claims (the empirical argument type described by Keil, 2010), contained abbreviations and other jargon, and were about twice as long. To illustrate, the positive and easy comment was written as follows:

Their method of estimating air pollution was pretty clever. Mothers whose workplaces were far from major roads would be exposed to less pollution, so taking that into account along with their home addresses allowed for a better estimate of exposure overall.

In contrast, the negative and hard comment was written this way (underlined text indicates a web link):

Their method of estimating air pollution was pretty poor. While they did control for the quantity of traffic, vehicle type was unaccounted for. Motor vehicle registration data shows significant differences in vehicle types throughout different states, and previous studies have shown a significant effect of vehicle type on CO, VOC, and PM emissions. Past studies have also shown that combining the International Vehicle Emissions (IVE) model with video road surveys provides an accurate breakdown of traffic-driven effects on air quality, which the authors failed to include in their own model.

In each condition, the headline and comment were displayed on a replica of an r/science page (See Figure 1). The post was set up to be 20 minutes old in order to foster agnosticism about the posts quality; it was meant to be recent enough that the cumulative upvotes would not be a useful indicator of public opinion about the article, while being old enough that at least one user could have feasibly read, digested, and commented on the article,

Measures. Participants' interest in reading the article were assessed on a 5-point Likert scale ("How likely would you be to read the article linked to in the previous screenshot?"). In order to ensure that participants actually found the technical jargon and empirical arguments to be more difficult to understand, we also included a manipulation check ("How easy or difficult was it to understand the comment in the previous screenshot?"), also on a 5-point scale.

All motivations indices were adapted from Park, Kee, and Valenzuela (Park, et al, 2009), with participants being asked to describe how strongly they agreed with the statements "I engage with science news (to feel connected to a community/to talk about research with others/to get useful information/to learn about topics I care about/because it's fun/because it's entertaining)." They were also asked how much they agreed with the statement, "I think Reddit is a good source of science news," as well as how often they visited Reddit and how often they read science news. Finally, all demographic questions were taken from Hughes, et al (2016).

At the beginning of the study, participants were instructed to “please go through the information just like you would normally if you were reading it on social media.” The next page contained the r/science screenshot, where participants read through the headline and comment described above. In the experimental conditions, once they navigated to the next page, participants were then asked whether or not they had read the comment. Once they responded, they were asked about the difficulty of the comment and their interest in reading the article.

4.3.2 Analysis

Analyses were primarily conducted under a Bayesian framework, as recommended for statistical analysis in HCI (Kay, et al, 2016), although frequentist statistics are presented as well for reference. Analysis was done using the rstan package for R. As per Winter, et al (2015), we condense our $2 \times 2 + 1$ conditions into a 1×5 ANOVA, and examine pairwise differences to disentangle interaction effects. Our linear model was a modified version of the robust Bayesian ANOVA offered by Kruschke (2014), with three modifications. First, while we retained the t-distribution for observations, we used a constant $\nu = 10$ rather than putting an exponential prior distribution on ν , which reduced divergent transitions during sampling. Second, we placed a uniform prior over σ , rather than a hierarchy of gamma distributions, also to reduce divergent transitions; the prior was placed over the range of 0-2 to allow for a wide range of realistic standard deviations. Third, we used a non-centered parameterization as described in the Stan User’s Guide, which can improve sampling efficiency and accuracy while providing an otherwise identical model. Using the notation $x[i]$ to indicate membership in one of the four comment conditions, our final model was defined as:

$$\begin{aligned}
 y &= t(10, \mu, \sigma) \\
 \mu &= \beta[i] + \alpha \\
 \sigma &\sim \text{uniform}(0, 2) \\
 \beta[i] &= \beta_{\text{raw}}[i]\sigma_{\beta}[i] \\
 \beta_{\text{raw}} &\sim N(0,1) \\
 \Sigma_{\beta} &\sim \text{gamma}(\alpha_{\gamma}, \beta_{\gamma})
 \end{aligned}$$

$$\alpha \sim N(M_y, SD_y)$$

Where α_γ and β_γ are shape and rate parameters chosen such that the gamma distribution has a mode equal to half the standard deviation of y , and a standard deviation equal to twice the standard deviation of y , as recommended by Kruschke (2014). Sampling was done using four chains of 25,000 iterations each, with 2000 iteration warm-up periods. All reported parameter estimates had effective sample sizes greater than 30,000, \hat{r} values less than 1.01, and the models had no divergent transitions during sampling. In all cases, parameters whose 95% credible intervals did not overlap with 0 were considered significant, foregoing the use of Bayes factors based on the discussion by Kruschke (2014). These credible intervals are based on central intervals using Stan's defaults.

	Interest in reading
Negative/hard	2.79 (1.39)
Negative/easy	3.22 (1.26)
Positive/hard	2.90 (1.45)
Positive/easy	3.04 (1.43)
Control	3.49 (1.06)

Table 2. Means and standard deviations of participants' interest in reading the article, by group.

Means and standard deviations for participants' interest in reading the article are provided in Table 2. Plots of posterior distributions over β_r values (referred to here as the deflection parameters, which indicate the difference from the control group) for the four experimental conditions are given in Figure 2. Our Bayesian model was applied as described above, with four deflection parameters for each of the four experimental conditions. Because of the differences in how multiple comparisons are handled under frequentist versus Bayesian frameworks (see Gelman, et al, 2012 for an in-depth discussion, or Kruschke, 2014 for applications to experimental research), our frequentist pairwise comparisons do not always match the Bayesian

ones in significance. However, for both Study 2a and Study 2b, we provide estimates from both frameworks to demonstrate robustness (or lack thereof) across multiple choices of analyses.

4.3.3 Results

Manipulation check. In order to ensure that our manipulation of difficulty (technical jargon, empirical arguments) was appropriate, we ran our model on participants' ratings of comment difficulty, comparing the effects of difficult comments vs. easy comments. Participants in the difficult comment conditions ($M = 2.57$, $SD = 1.13$) rated the comment as being significantly more challenging to understand than participants in the easy comment conditions ($M = 2.09$, $SD = 1.14$), $d = 1.68$, indicating a very large effect. Thus, the experimental manipulation was successful.

Valence. We found that H1, predicting that a negatively valenced comment will decrease people's interest in reading, is not supported. Specifically, our analyses showed that while the negative/hard comment showed significant deflection from control, $\beta = -0.58$ $[-1.08, -0.10]$, the negative/easy comment was not significant, $\beta = -0.14$ $[-0.58, 0.27]$. We also failed to support H2, which predicted that participants who were motivated by the information utility of science news would show reduced interest in reading the article following a negative comment. Motivation scores were calculated using the statistical average of the inventory items. The interaction (information \times valence) was not significant ($p = .193$).

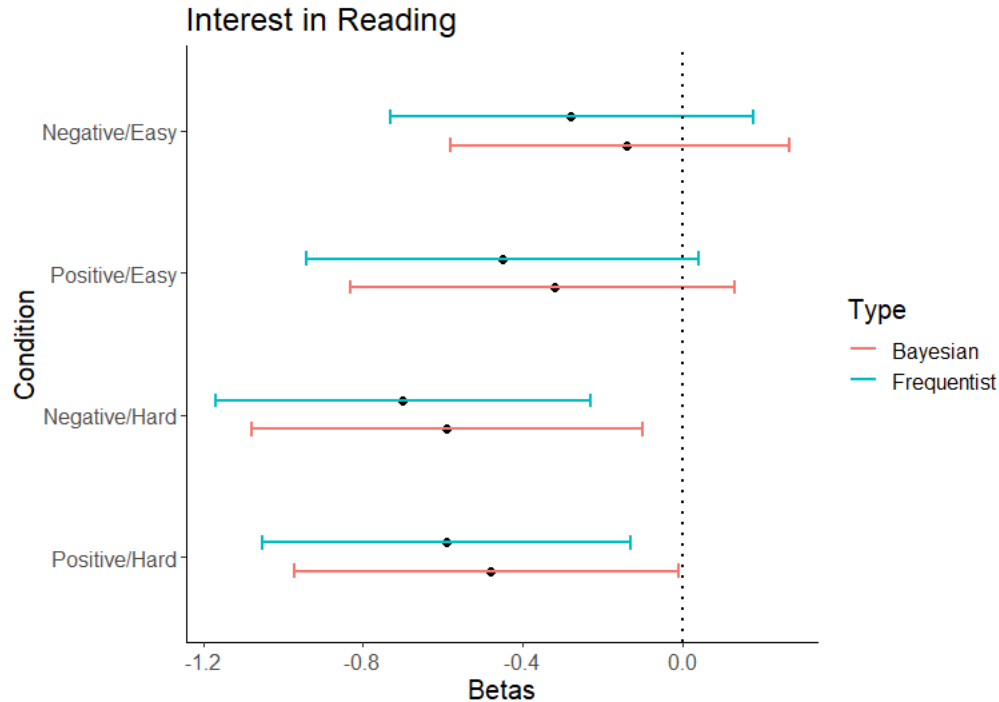


Figure 2. Bayesian credible intervals and frequentist confidence intervals over the beta values describing the average change in likelihood to read for (from top to bottom) negative/easy, positive/easy, negative/hard, and positive/hard comments compared to control. The greater the distance between the CIs and 0, the greater confidence we have that the results for that condition are different than the control condition. Here, both difficult comments cause significantly decreased interest in reading compared to control.

Difficulty. Finally, we support H_{3a} (and reject H_{3b}), which predicted that difficult comments would cause decreased interest in reading the article. The positive/hard comment showed significant deflection from control $\beta = -0.48 [-0.97, -0.01]$, as did the negative/hard comment as described above. This is mirrored by a significant frequentist ANOVA, $F(4, 293) = 2.68, p = .032, \eta_p^2 = 0.035$, indicating a small effect. Furthermore, in terms of SRQ1, we do not find evidence that the positive conditions improved participants' interest in reading the article. To ensure that participants' previous exposure to science news was not responsible for this result, we also ran an ANCOVA using how often participants read science news as a control variable, $F(4, 293) = 2.91, p = .022$. Results mirrored the above, with the negative/hard ($p = .004$) and positive/hard ($p = .025$) conditions remaining significant under this model, suggesting our results were not caused by this individual difference.

Interestingly, while only the difficult comments yielded significantly reduced interest in reading compared to the control, all four comment conditions trended in the negative direction, and pooling all comments into a single predictor in our Bayesian model shows that seeing any of the four comments, on average, decreased participants' interest in reading the article, $\beta = -0.46$ $[-0.84, -0.07]$. I will address this general trend in the general discussion section (4.5).

4.3.4 Discussion

Study 2a showed how user-generated comments can affect people's interest in reading the associated article; interestingly, and in contrast with our expectations, our findings suggest that reading both positive and negative comments---specifically difficult comments---may reduce people's willingness to read the article, rather than the main effect of negative comments that we predicted. While past research has noted multiple negative effects of difficult scientific text, and we indeed show that the presence of difficult comments can reduce people's interest in reading the article, it is not clear precisely what accounts for this effect in this context.

One explanation may be that reading a difficult comment could signal that the article itself is more difficult, which could explain why both difficult article conditions showed significantly reduced likelihood to read; given that people tend to avoid texts they expect will be more difficult (Smith, 2000), a comment that provides this signal could deter them from reading. It may also be that they feel less connection to science in general after reading a difficult comment (Shulman, et al, 2020), which could also contribute to this effect.

I will also note here that difficult comments did not increase people's interest in reading the article, despite the potential consequences of the easiness effect (Scharrer, et al, 2017). Perhaps even if participants did feel less confident about their understanding of the study prior to reading it, they may not have felt like reading the article would have been helpful in understanding it (e.g. if the above explanation is correct and they assumed the article would be just as difficult to understand). In that case, there would be little utility in reading the article, as reading an equally difficult text may do little to improve their understanding.

Ultimately, the results of Study 2a show a general trend for our difficult comments to reduce participants' likelihood to read. However, the reason for this effect remains unclear. Thus, Study 2b is an attempt to glean insight about the potential reasons reading comments might affect how likely people are to read the article.

4.4. Study 2b: Difficulty, Information Quality, and Arousal

Study 2b provides a deeper look into the different types of comments that can impact people's interest in reading science articles, and what mediating variables may be responsible for this effect. While there are a number of potential explanations for the effects of difficult comments to reduce people's interest in reading the associated article in Study 2a, including increased expectations of the article's difficulty or reductions in its expected information quality, we lacked the data to explore these possibilities. Thus, our second experiment was a pre-registered, confirmatory follow-up testing these possible explanations and clarifying the effects of user comments on people's perceptions of science articles.

4.4.1 Hypotheses

In Study 2a, we found evidence that reading a difficult comment before a science news article can impact people's interest in reading that article, but were unable to conclude what may have been driving this effect. In Study 2b, we both extended and deepened our understanding of the ways in which different comments can impact people's interest in reading science articles, by examining three distinct features: difficulty, information quality, and entertainment. By examining comments that vary along these three dimensions, and exploring their effects on a number of potential mediating variables, we could better determine what may have accounted for the effects we observed in Study 2a.

Difficulty. First, in terms of difficulty, I expected that our results from Study 2a would replicate. However, there are a few possible mechanisms for this effect. First, past research has found that the presence of comments can impact people's expectations of an article's quality (Prochazka, et al, 2018), based on certain heuristic cues (Waddel, 2020). Perhaps when viewing user-generated comments, people utilize a similarity heuristic (Sundar, 2008), whereby certain information (in this case, a comment) is being used as a signal for the type of information to expect (in this case,

the article). If this were the case, it may be that if people read a difficult comment, they will expect that the article itself will be difficult to understand, thus reducing their interest in reading it. Thus:

H4a_α: People who read a difficult comment will expect the article to be more difficult to read than those who read less difficult comments.

However, given that recent work has found that the use of jargon can reduce people's self-reported connection to the scientific community, as well as their interest in science at all, these constructs may also come into play when people read more technical comments. Further, if jargon reduces people's interest in science, they may no longer consider scientific articles as personally relevant, due either to feelings of alienation from science (Thompson & Windschitl, 2005), difficulty finding personally useful information (Pirolli & Card, 1999), or the assumption that more technical articles are not written for public consumption. This in turn could reduce their interest in reading the article if they are motivated by personal interests or affirmation (O'Brien, et al, 2013):

H4a_β: People who read more difficult comments will show less connection to the scientific community, less interest in science in general, and less interest in the specific article than people who read easier comments.

In either case, I expected that people who read more difficult comments will show less interest in the article than people who read easier comments.

H4b: Participants who read more difficult comments will show less interest in reading the article.

Information quality. As noted above, prior work (Prochazka, et al, 2018) has suggested that user comments may signal something about the quality of an article. Given this, it may be that after reading a comment that is poorly-written or unhelpful, one may assume that the article it is associated with will also be low-quality. While previous research has examined "quality" both in

terms of "formal quality" (i.e. how well an article was written) as well as "informational quality" (i.e. how useful and accurate the information in an article will be), I expected that this latter quality will be more closely associated with people's likelihood to read an article, given the importance of information motivation in selecting online news (O'Brien, et al, 2013). Thus, I expected that if a comment contains useful information, it will signal to readers that the article will be similarly useful. That is:

H5a: Participants who read comments with low-information quality will expect the article to contain less useful information than participants in other conditions.

H5b: Participants who read comments with low-information quality will be less likely to read the article.

Entertainment. Finally, one of the most common motivations for reading online news is entertainment (O'Brien, et al, 2013). Because of this, I expected that if reading an entertaining comment provides a signal that the article itself may be more entertaining, people who read entertaining comments may be more interested in reading their associated article. Thus:

H6a: Participants who read more entertaining comments will expect that the article will be more entertaining as well.

H6b: Participants who read the more entertaining comment will be more likely to read the article.

H6c: There will be an interaction such that participants who are more entertainment-motivated will be affected by entertaining comments than participants who are not.

4.4.2 *Methods*

Study 2b utilized a 3 (easy vs. low information vs. entertaining) + 1 (Base comment) + 1 (Control) experimental design. Rather than using a fully crossed design as in Study 2a (which would have required a total of 9 conditions, and a prohibitively large sample size), we instead

designed a base comment meant to reflect a typical r/science comment (Jones, et al, 2019). This allowed us to compare each of the experimental conditions with a comment that varied along one of the experimental dimensions, as well as a no-comment control as in Study 2a. It was pre-registered here: https://osf.io/pq9v5?view_only=a57d43b09ab14f938d6c18d9fe36d613.

Participants. We recruited a total of 423 participants on Amazon Mechanical Turk. We again included multiple attention checks, and sampled participants until we retained a total of 286 (age: $M = 35.0$, $SD = 10.57$). 192 of our participants identified as male, 90 identified as female, 1 identified as non-binary, and 3 chose not to specify. The sample was 66.5% (176) White, 21.0% (60) Asian, 5.6% (16) Black or African American, 4.9% (14) Hispanic or Latino, 0.4% (1) American Indian or Alaska Native, and 0.4% (1) Native Hawaiian or Pacific Islander. 54.5% (156) reported using Reddit at least once a day, and 82.5% (236) using at at least once a week. These numbers were notably lower for r/science usage, with only 11.5% (36) visiting the subreddit once a day, and 38.5% (110) once a week.

Stimuli. As per Study 2a, we chose a science news article and created an r/science mockup of it. This new article discussed the relationship between having a more optimistic romantic partner and long-term cognitive health. Comments varied based on how much information they contained, how much technical jargon they contained, and the tone of the writing (see Table 3). The base comment was designed to mimic typical popular comments on r/science (Jones, et al, 2019), and contained useful information about the study, technical jargon, and was written in a non-arousing manner. The easy comment was identical to the base comment, but replaced the technical jargon with plain-language explanations of the concepts. In contrast, the low-quality information comment contained a positive evaluation of the study, but no other information. Finally, the entertaining comment contained more exclamations (to increase arousal, which is related to entertainment; Oliver & Bartsch, 2010) and jokes.

Comment	Difficulty	Information	Entertainment	Text
Base	High	High	Low	This study was actually pretty strong, and the evidence seems to suggest a clear link between having an optimistic partner and long-term health. By using a large sample (N = 8,914; M age = 66.73, SD = 9.67) from the longitudinal HRS database over 8 years (t1; t2; t3; t4; t5), as well as multilevel dyadic analysis to account for non-independence in their data, they find significant associations between partner optimism and actor cognitive functions like memory (r = .04, p < .05) and mental status (r = .03, p < .05) while controlling for possible confounds. Overall, it appears to be a small but clear effect.
Easy	Low	High	Low	This study was actually pretty strong, and the evidence seems to suggest a clear link between having an optimistic partner and long-term health. By using a large sample with nearly 9,000 participants from the Health and Retirement Study database over 8 years, as well as using advanced statistical techniques, they find significant associations between a person's partner's optimism and that person's cognitive functions like memory and mental status, while controlling for other economic and health factors. Overall, it appears to be a small but clear effect.
Low-quality	Low ¹	Low	Low	This study was pretty good.
Entertaining	High	High	High	This study was actually really cool! It's a convincing case for a link between having an optimistic partner and long-term health (makes me think I should put "glass half full people only" on my Tinder profile...). By using a large sample (N = 8,914; M age = 66.73, SD = 9.67) from the longitudinal HRS database over 8 years (t1; t2; t3; t4; t5), as well as multilevel dyadic analysis to account for non-independence in their data, they find significant associations between partner optimism and actor cognitive functions like memory (r = .04, p < .05) and mental status (r = .03, p < .05) while controlling for possible confounds. Overall, it appears to be a small but clear effect.

Table 3. Description of comment types.

¹ Because of its lack of content, the low-quality comment was also easy to understand. Mediation analysis ensures that our experimental results for this condition were driven by differences in information quality rather than difficulty.

Measures. All previous measures from Study 2a were retained, and all new measures were 5-point Likert scales, except where specified. We measured information quality for both the comment and the article using an index adapted from Bobkowski, 2015 (e.g. "How [helpful/valuable/useful/informative] do you think the information in the article will be?"). We also adapted questions about people's interest in science ("How interested are you in scientific topics in general?") and people's identification with science ("I am good at science," "It is important to me that I am good at science") from Shulman, et al. (2020). Additional variables included people's interest in the article's subject ("How interested are you in the article's topic?"), the importance of the article's subject ("How important do you think the article's topic is?"), the expected difficulty of the article ("How difficult do you think it would be to understand the article?"), and the expected entertainment value of the article ("How entertaining do you think the article will be?"). We also added manipulation checks for comment information quality and comment entertainment value. These were displayed immediately before participants read the article, as in Study 2a.

We also added a set of open-ended questions for participants to fill out, after the post-article DVs. These asked for their expectations about the article ("Thinking back to when you first saw the Reddit snapshot, how did the information on the page (the headline, any comments you saw, etc.), affect what you thought about the article?") and their likelihood to read the article specifically ("How, if at all, did that affect your likelihood to want to read the article?").

In every other way, the design of Study 2b was identical to Study 2a.

4.4.3 *Analysis*

Our Bayesian model was identical to Study 2a, except that in order to reduce divergent transitions, we tuned our model to have a slightly tighter prior over σ_β by multiplying the rate parameter of the gamma distribution by 1.5, one of several strategies recommended for dealing with divergences (Modrak, 2018). Sampling was done with 4 chains of 15,000 iterations each, with 2000 iteration warm-up periods. All reported parameter estimates had effective sample sizes greater than 20,000, r-hat values less than 1.01, and no divergent transitions. As in Study 2a, we provide frequentist tests for reference.

Our pre-registered analyses included using our Bayesian model to analyze each of our DVs and mediators, combined with frequentist ANOVAs. Because the dimensions of our experimental manipulation (difficulty, information quality, entertainment) were not fully crossed, we utilized a modified Dunnett's test (Bretz, et al, 2016) for our frequentist models to compare each experimental condition to both the base comment condition and the no-comment control condition, without comparing the experimental condition to each other. Because we did not apply family-wise error rate corrections to the Bayesian models, I report multiple comparison results as-is between the experimental and control conditions, but again I do not report comparisons between the experimental conditions.

I also provide exploratory mediation and path analyses (note that these were not pre-registered). I discuss these results along with our qualitative data to help clarify the experimental effects we observed.

4.4.4 Results

Manipulation Checks. First, our difficulty manipulation was successful. Specifically, there were significant deflections for both the easy comment $\beta = -1.73$ [-2.08, -1.37], as expected, and the low-quality comment $\beta = -1.70$ [-2.06, -1.35] (likely due to its short length and lack of information). These results were echoed by a significant ANOVA, $F(3, 223) = 46.72$, $p < .001$, $\eta^2_p = .386$), suggesting a very strong effect.

Our information quality manipulation was also successful, with significant effects for both the low-quality comment, $\beta = -1.10$ [-1.44, -0.77], as well as the entertaining comment, $\beta = -0.46$ [-0.78, -0.14], supported by a highly significant anova, $F(3, 223) = 22.60$, $p < 0.001$, $\eta^2_p = .285$, indicating a large effect. Although the manipulation for the low-quality comment was successful, it may be that the presence of humor in the entertaining comment reduced participants' impressions of the information provided in that comment as well, which may impact how the entertaining comment affected their impressions of the article itself beyond the intended manipulation.

Moving on to entertainment, we did not detect a significant difference between the entertaining comment and the base comment, $\beta = -0.01 [-0.40, 0.37]$ (frequentist $\mu_{\Delta} = -0.03$, $p = .999$), suggesting that this manipulation was not successful. However, there were significant differences between the easy and base comments for entertainment value, $\beta = 0.48 [0.04, 0.93]$ (marginally significant under the frequentist model $\mu_{\Delta} = 0.48$, $p = .077$), suggesting that the easy comment was perceived as more entertaining than the base (i.e. more difficult) comment.

Difficulty. Starting with difficulty (see Figure 3), our results support H4a_α. We find that the base (i.e. difficult) comment increased expected article difficulty compared to the easy comment, $\mu_{\Delta} = -0.62 [-1.06, -0.18]$. The difficult comment also showed significant deflection from control ($\beta = 0.64 [0.21, 1.06]$), with an overall significant frequentist anova ($F(4, 281) = 4.89$, $p = .011$) and a marginally significant difference between the easy and base conditions ($\mu_{\Delta} = -0.58$, $p = .062$).

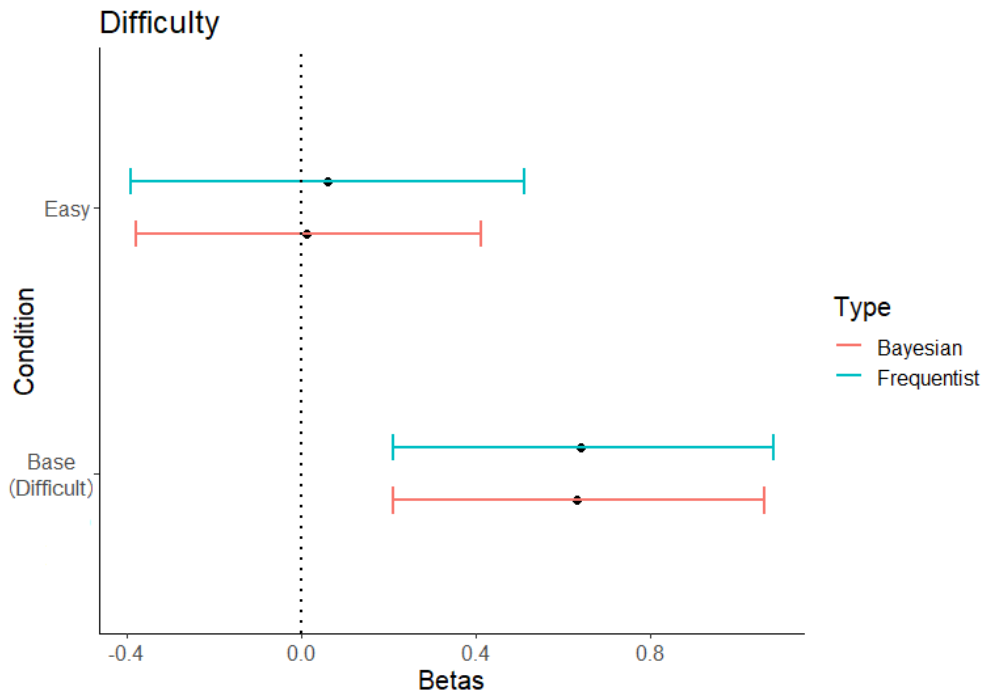


Figure 3. Bayesian and frequentist CIs over effects of comment types on expected article difficulty.

Moving on, our results only partially support H4a_β. Participants who read the more difficult (base) comment showed a decreased interest in science compared to the easy comment, $\mu_{\Delta} = 0.34$

[0.02, 0.67]. However, the frequentist ANOVA was not significant, $F(4, 281) = 1.45$, $p = .217$, $\eta^2_p = .020$, suggesting that this effect was not strong enough to show robust significance given our sample size. Moreover, there were no effects on participants' science identity via either framework, with a non-significant frequentist ANOVA $F(4, 281) = 0.59$, $p = .668$, $\eta^2_p = .008$. There were also no significant pairwise effects on their interest in the article's topic via either framework, but the ANOVA was significant in this case, $F(4, 281) = 2.42$, $p = .049$, $\eta^2_p = .033$. Overall, because of the disagreement between the Bayesian and frequentist frameworks, and the partial support for an effect on science and subject interest but not on science identity, we consider H4a_β to be only somewhat supported.

Finally, we look at participants' interest in reading the article (see Figure 5), with results supporting H4b. Participants in the easy condition showed significantly more interest in reading the article than participants in the base (difficult) condition under both the Bayesian ($\mu_\Delta = 0.65$ [0.20, 1.11]) and frequentist ($\mu_\Delta = 0.64$, $p = .026$) frameworks (although neither were significantly different from control under either framework), with a significant overall ANOVA $F(4, 281) = 3.31$, $p = .011$, $\eta^2_p = .061$ indicating an effect size somewhat larger than Study 2a (although still relatively small).

Information quality. Moving on, our results support H5a; we found that the low-quality comment significantly reduced participants' expectations of the article's information quality (see Figure \ref{art_qual}), $\mu_\Delta = -0.44$ [-0.72, -0.17], although the difference between the low-quality and control condition did not quite reach significance $\beta = -0.25$ [-0.52, 0.02]. The frequentist ANOVA was also significant, $F(4, 281) = 6.54$, $p < .001$, $\eta^2_p = .085$, with a significant difference between low-quality and base conditions ($\mu_\Delta = -0.52$, $p = .003$). However, we failed to support H5b; there were no significant differences between the low-quality comment and either comparison condition on participants' interest in reading the article (see Figure 4).

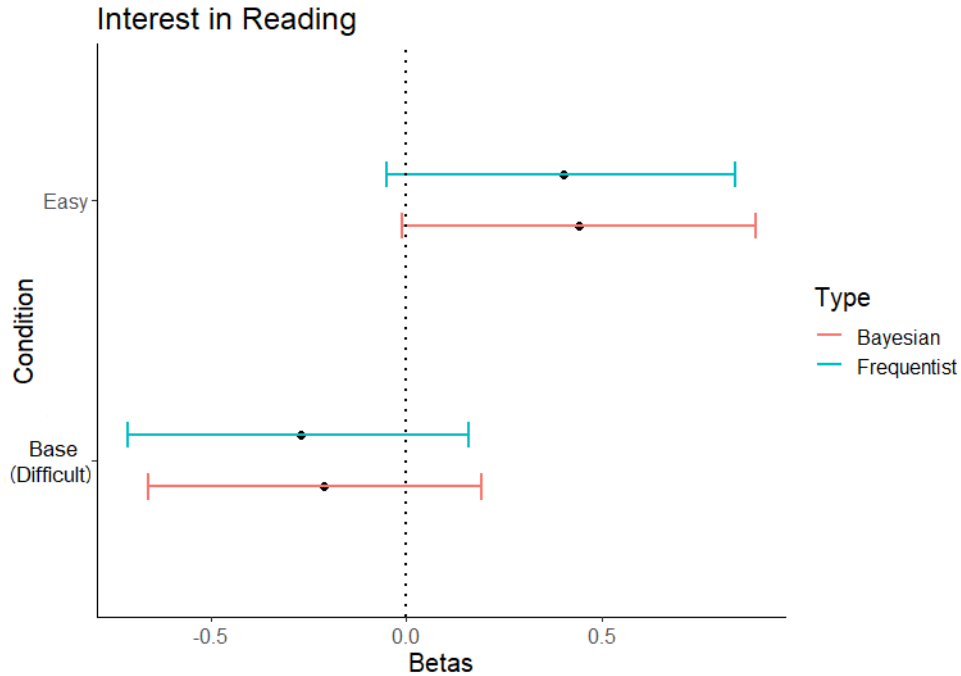


Figure 4. Bayesian and frequentist CIs over effects of comment types on interest in reading the article.

Because the low-quality comment was also significantly easier to understand than the base comment, we use mediation analysis to ensure that our experimental results were accounted for by the difference in information quality, rather than any possible effect of difficulty (see Section 4.4.5 for more details on our mediation analysis methods). Indeed, we show that the effect of the low-quality comment on expected article quality was significantly mediated by the comment's quality (average causal mediated effect (ACME) = -0.62, $p < .001$).

Entertainment value. Because the manipulation check for the entertaining comment was unsuccessful, we use participants' ratings of the comments' entertainment value as a predictor for their expected article entertainment value instead to test H5a (see Table 4). Indeed, we show that participants' expectations for the article's entertainment value was significantly predicted by their assessment of the comment's entertainment value, supporting H6a. Note that was an ad-hoc analysis, and is correlational data, so although it is compelling, it is difficult to make any causal inference.

Predictors	Estimate	CI [95%]	p
(Intercept)	1.18	[0.93, 1.42]	< .001
Comment entertainment	0.68	[0.58, 0.78]	< .001
Observations	286		
Adjusted R²	= .468		
p	< .001		

Table 4. Summary of linear model on participants' expected article entertainment value as a function of their perceived comment entertainment.

Moving on to H6b, we also find that comment entertainment significantly predicted participants' interest in reading the article (see Table 5), tentatively supporting this hypothesis (although this main effect loses significance under the interaction model, see below). We also hypothesized that entertainment-motivated participants would be more motivated to read articles after reading high-arousal comments. Again, because the entertaining condition failed our manipulation check, we examined the interaction term between entertainment motivation and comment entertainment value; however, there was no significant interaction ($p = .461$), so H6c was also not supported.

Predictors	Estimate	CI [95%]	p
(Intercept)	1.81	[1.52, 2.10]	< .001
Comment entertainment	0.55	[0.44, 0.67]	< .001
Observations	286		
Adjusted R²	= .292		
p	< .001		

Table 5. Summary of linear model on participants' interest in reading the article as a function of their perceived comment entertainment.

Mediation tests. For our mediation tests, we employ Tingley, et al.'s (2014) mediation package for R. This allows us to estimate the *average causal mediation effects* (ACME), and the *average direct effects* (ADE) for each level of the "treatment" variable (in this case, different comment types). A significant ACME suggests that a significant amount of the effect of some variable X on outcome variable Y is mediated by some variable M. A significant ADE, on the other suggests, that there is a significant effect of X on Y after controlling for M. Because we did not pre-specify our models in our pre-registration, and because we made ad-hoc adjustments to our analyses in order to better disentangle our effects, all proceeding analyses should be considered exploratory. All analyses are bootstrapped simulations using 10,000 iterations each. Each mediation test was done using one of the experimental conditions as a predictor, comparing against the base and control comments as a baseline.

First, we investigated whether the change in expected article difficulty mediated by the positive effect of reading easier comments (see Table 6). However, there was no significant mediated effect, although the overall difference between the easy comment and the baseline comments was significant. We also examined the potential mediating effect of expected entertainment value, but unsurprisingly, there was also no significant mediating effect, given that even the easy condition failed to significantly increase this variable. However, because of the significant effect of the easy comment on expected information quality, we examined information quality as a mediator as well, and found that it did significantly mediate the positive effect of the easy comment, with the easy comment leading to increased expected information quality, and consequently, higher interest in reading the article. We will examine this effect further in the proceeding section.

We also examined the difference between the low-quality comment and the baseline comments, due to its strong effect on information quality. Similar to the easy comment, we found that the low-quality comment's effect was also significantly mediated by expected information quality, although in the opposite direction; reading the low-quality comment reduced people's expectations about the article's information quality, which reduced their interest in reading the article, although as the non-significant total effect and experimental results show, the overall effect was not strong enough to show significance in this case.

Difficulty (Comment) -> Difficulty (Article) -> Interest in reading			
Quantity	Value	CI [95%]	p
ACME	-0.04	[-0.14, 0.02]	= .246
ADE	0.57	[0.19, 0.95]	= .004
Total effect	0.53	[0.15, 0.92]	= .006
Proportion mediated	-0.06	[-0.49, 0.05]	= .250
Difficulty (Comment) -> Difficulty (Article) -> Interest in reading			
Quantity	Value	CI [95%]	p
ACME	-0.23	[-0.43, -0.07]	= .004
ADE	0.06	[-0.31, 0.44]	= .755
Total effect	-0.17	[-0.57, 0.23]	= .391
Proportion mediated	0.87	[-10.17, 12.26]	= .392
Difficulty (Comment) -> Difficulty (Article) -> Interest in reading			
Quantity	Value	CI [95%]	p
ACME	0.18	[0.04, 0.35]	= .013
ADE	0.35	[-0.02, 0.72]	= .065
Total effect	0.53	[0.14, 0.92]	= .007
Proportion mediated	0.34	[0.08, 1.06]	= .018
Difficulty (Comment) -> Difficulty (Article) -> Interest in reading			
Quantity	Value	CI [95%]	p
ACME	-0.04	[-0.20, 0.12]	= .667
ADE	0.57	[0.21, 0.92]	= .002
Total effect	0.63	[0.14, 0.93]	= .008
Proportion mediated	-0.06	[-0.83, 0.22]	= .675

Table 6. Summary of mediation analyses.

While these analyses provide some insight into the effects of different comment types on participants' interest in reading the article, the relationships between our full set of mediators, and how they lead participants to read or avoid associated articles, is still unclear. We next turned to structural equation modeling (SEM) to better clarify a possible structure whereby our experimental manipulation and observed mediators impacted participants' self-reported likelihood to read the article.

Structural equation modeling. We began by examining a model relating the comment variables (difficulty, information quality, and entertainment) with the article variables (information quality, difficulty, entertainment, and topic interest), which in turn predicted interest in reading. We included participants' overall interest in the article's topic as a predictor, allowing us to control for this variable in the regressions and improve model fit. After dropping variables which showed no relationship with any outcome variables and making ad-hoc adjustments to ensure good model fit, we fit the final model (see Figure 5) as follows:

$$\text{read} \sim \text{difficulty}_a + \text{info}_a + \text{entertainment}_a + \text{topic interest}$$

$$\text{info}_a \sim \text{difficulty}_a + \text{info}_c + \text{topic interest}$$

$$\text{Entertainment}_a \sim \text{entertainment}_c + \text{topic interest}$$

$$\text{difficulty}_a \sim \text{difficulty}_c$$

where the subscript *a* indicates the expected value of that variable for the article, and the subscript *c* indicates the perceived value of the comment. While the model fit was acceptable (CFI = .963, SRMR = .069, RMSEA = .080), another important criterion for evaluating SEMs is their theoretical interpretability (Lei & Wu, 2007), so I will briefly discuss our modeling choices and interpretation as I discuss results.

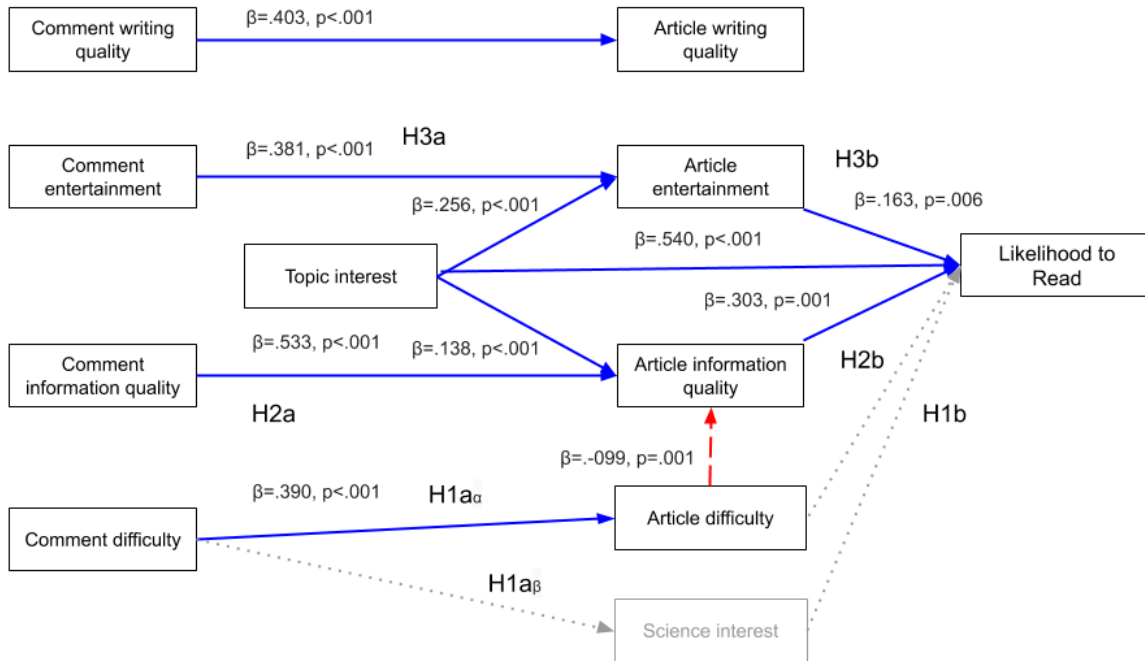


Figure 5. Path diagram describing our model of mediating variables on participants' interest in reading the science article. Solid blue lines indicate a positive relationship, whereas dashed red lines indicate a negative relationship. Overall, we observed that comment attributes signal that the article will share similar attributes, each of which may somehow affect their final decision to read that article. I included unsupported hypothesized paths (dotted gray lines) for illustrative purposes, although they were not included in the final SEM specification due to lack of experimental support and negative effects on model fit.

Overall, because our experimental results showed that participants who read comments of a certain attribute (e.g. more technically difficult, more useful information) showed higher expectations that the article itself would have those attributes (e.g. participants who read the easy comment expected the article to be easier to understand), we modeled those article mediators as being predicted by their comment-based counterparts. Furthermore, it stands that the expected entertainment and informational value of an article will both depend on how interested one personally is in the topic, a relationship which we see here.

If we consider the overall rate of information gain as a ratio of the value of the information over the cost of retrieving it (Pirolli & Card, 1999), we would expect that information quality would be negatively impacted by expected article difficulty; if an article is more difficult to understand, it may not be considered as useful, since the information within it becomes harder to parse. Indeed, we can see a negative relationship between information quality and difficulty in our model.

We also expected that the four primary article mediators would all be associated with participants' interest in reading it. However, in this case, only entertainment and information quality were significant, although difficulty may still have an indirect relationship via its reduction on expected information quality.. However, topic interest itself did show a strong relationship with interest in reading, somewhat unsurprisingly. Overall, we show that the attributes of a comment seem to be related to participants' expectations for the article, many of which may be linked to their likelihood to read it.

Qualitative results. For each comment condition, I coded participants' answers to the open-ended questions as to whether they mentioned the comment, and if so, whether it increased or decreased their likelihood to read the article. Overall, we found that participants drew a number of inferences about the article from the different comment types, largely supporting our quantitative findings. Quotes are lightly edited for grammar and spelling.

First, in our quantitative analyses, we found that difficult comments may be used heuristically to infer article difficulty. In our qualitative responses, participants mentioned how the more technical and difficult comments can affect their perceptions of the article and subsequent likelihood to read it:

The comment was too scientific and too wordy...It made me think that the article had too many scientific terms and that it would be confusing and hard to understand, so the comment made me not want to read the article initially.

I did not want to read the article if it was filled with terms that I could not easily understand. Having to research the terms would have been too much of a hassle for me to read about this topic.

Similarly to comment difficulty, we also found that comments' information quality affected the perceived information quality of the article.

Having only one short comment without any information about it made me think poorly about the article...The poor comment probably would make me skip reading the article.

The comment was super descriptive and informative and made me think that there was a lot of worthy information to be found in the article...Sometimes I read the comment sections of an article first to see what other people think of it, so yes a very well written informative comment would for sure affect the likelihood of myself reading an article.

However, participants also reported some other relationships that we did not explore and deserve future examination. First, there seemed to be an effect of summarizing too much information, with some participants mentioning that they felt like the comment had enough information that they would no longer be interested in reading the article itself:

I felt like I got a nice summary of the article in the comment and felt it not necessary to have to read the full article so I would have never clicked on the link myself or have shared it.

Second, although not found in our model, participants did report topic interest as a potential moderator.

If the topic was something that I was very passionate about then having to do extra research would not be a problem.

4.5 Discussion

In Chapter 3, I examined the potential of participatory web platforms for science communication from the researchers' perspective, discussing potential designs that could assist them in doing this work. Here, I further addressed RQ1 by examining the question of platform affordances from the user perspective; in particular, how discussions around science news affect people's expectations for—and interest in reading—science news articles.

Across two experiments, we identified numerous effects of user-generated comments on people's expectations of science news articles. We saw that reading user comments before an article can signal the difficulty, information quality, and entertainment value of an article. Specifically, we found that people utilize a similarity heuristic; they infer that the article will hold similar characteristics as the article's comments (e.g. difficulty). While some previous research (e.g. Winter, et al, 2017; Anderson, et al, 2014) has examined the effects of user commentary in a science news context, they were done using a typical blog format with comments presented after the article. Here, we showed that when people read the comments first (as many do on sites like Reddit; Jones, et al, 2019), it can color their perception of the article in numerous ways.

Our studies also helped elucidate the impact these perceptions of the article may have on people's likelihood to read the articles. Through our path analyses, we found that perceived article entertainment value and information quality both directly increase people's interest in reading the article. Article difficulty, however, did not have a direct effect. Rather, it decreased interest in reading by reducing the expected information quality of the article.

This similarity heuristic towards online news is understandable. Because of the vast amount of information online, people are going to rely on heuristics to help them determine how to allocate their attention (Sundar, 2008). In a comment-first design, people will utilize the available information (i.e., the comments) to help them make their inferences. However, problems arise when the qualities of the comments do not match the qualities of the articles. This could lead to people reading bad science because others have provided high quality comments, or more problematically, high quality articles being overlooked because of low-quality comments. Furthermore, as we found, the low-quality comments may not just influence likelihood to read,

but also how strongly people agree with the study's methods or findings. This also means that campaigns to discredit science can be extremely effective in the comment-first design. Low quality comments may not only turn people away from the articles, but also make them think poorly of the studies themselves.

As in Chapter 3, I'll discuss a few direct design implications based on our results, before turning to discuss how these studies have helped answer RQ1, and how they inform further research explored in this dissertation.

4.5.1 Design implications

Our findings suggest a number of design implications for science news communities. Had we found evidence that an "easiness effect" (Scharrer, et al, 2017) in user comments would discourage people who read easy comments from seeking out more information, it may have been useful to highlight such comments on communities like r/science. However, given the overall negative effect of difficult comments in Study 1 and the difference between easy and difficult comments in Study 2, we suggest the opposite; these communities should explicitly discourage overly-technical comments, which could prevent them from signaling that an article is more difficult, and thus less informative, than it may actually be. Currently, r/science has no guidelines on the use of technical language for comments, and this could have the added benefit of ensuring that discussions are accessible to non-expert audiences as well, although balancing accessibility with scientific rigor is a well-known challenge (Ecklund, et al, 2012; Jones, et al, 2019; Sharon, 2014). Another solution could be for sites to automatically detect difficult comments and reduce their likelihood of being displayed up-front. This could be done via automated methods, either through sophisticated natural-language processing, or basic keyword-matching to identify technical jargon based on a pre-defined dictionary (Siddharthan, 2014). Of course, such a system should ideally be made explicit to the community and combined with written guidelines, to ensure that users' content is not suppressed in an opaque manner without their understanding.

Of course, we also found that the expected information quality of the article was the most direct mediator for people's interest in reading. So, because we found that the quality of the comments

can signal the quality of the article itself, ensuring the comments people see before reading an article are themselves high-quality may be important. As it is, many social media sites provide these comments up front, which may encourage people to read them first (Jones, et al, 2019), so ensuring those comments reflect well on the article is key. However, while r/science's moderation combined with Reddit's up-vote system typically ensure that high-quality comments are the most visible, other science communication communities on platforms like Facebook may not self-curate quality content as effectively (Bloomfield & Tillery, 2019). As our study highlights, such communities should likely prioritize placing high-quality discussion up-front, and making such priorities explicit to the community.

However, our qualitative results suggest that some people may use the comments as a summary of the article itself, making them feel like they don't need to read the article at all. To side-step this potential issue, science communication platforms could consider ways of signaling these attributes without requiring users to read the comments themselves. For example, rather than a simple up-vote/down-vote system, platforms could implement more nuanced feedback about an article's quality, such as its technical difficulty, scope, validity, and depth of information, which could be available at a glance without needing to dive into the comments section. By allowing users to "up-vote" an article along one of the dimensions we found that could affect their interest in reading the article, more useful information about the article could bubble up, allowing users to make informed decisions about whether an article is worth reading, given their background, interests, and motivations.

Furthermore, by surfacing this information, platforms may be able to avoid potential spiral-of-silence (Noelle-Neumann, 1974) dilemmas. The spiral-of-silence, whereby people's assumptions of popular opinion prevent them from discussing contentious topics, can be a significant problem for science communication (Priest, 2006). If users read a low-quality comment or difficult comment, they may decide not to read the article itself, coming away with an incomplete or false impression of the article (Hlavach & Freivogel, 2011). This could be especially problematic given the tendency for people to assume that comments reflect public opinion (Waddel, 2020); an inaccurate comment may dissuade people from reading an article, while simultaneously providing an inaccurate impression of public opinion, potentially

dissuading people from discussing a topic or voicing alternative opinions (Noelle-Neumann, 1974). Through such a mechanism, user comments may have a significant impact on people's final impressions of a research finding, and low-quality or poorly-reason comments that promote negative attitudes toward science (e.g. climate change denial) may dissuade people from reading science articles and impact their opinions of relevant topics. Thus, providing mechanisms to reduce the negative effects of certain user comments and encouraging people to read science articles will help ensure such misunderstandings are minimized, and improve science communication on social media platforms like Reddit.

4.6.2 Answering RQ1

RQ1 asked “How do the affordances of participatory web technologies affect the way science information is conducted, perceived, and engaged with?” Chapters 3 and 4 examined this question from the perspectives of researchers who use the platforms to reach the public (3) and social media users deciding whether to engage with scientific work (4). By doing so, we can start to think about two main gaps, coinciding with an engagement model of science communication (Trench, 2008).

The first gap involves the difficulty that researchers have when trying to reach various publics on the participatory web. This included challenges *targeting* specific groups when publishing posts, blogs, or videos; *knowing* what kinds of people are in one's typical audiences; and using that information to *frame* one's work effectively within the constraints of a given platform. Researchers may see the value in science communication, but it's not always clear how to do so effectively, despite the massive potential of participatory web platforms.

The second gap involves domain non-experts accessing, engaging with, and using scientific information on the participatory web. Through studies 2a and 2b, I've shown that one of the defining features of participatory web platforms—user-generated comments—can strongly shape one's expectations about science news information, affecting users' interest in reading it. Given how technical and unwelcoming discussions around scientific topics can be (Jones, et al, 2019), this can reduce people's *access* to scientific information online. Even if one does the work of

writing science news articles and targeting a community like r/science, the discussion that frames the article can itself be a barrier for the reader.

To address the first gap, the next chapter will examine how designing an audience analytics tool can solve many of the issues researchers face on the participatory web. That coincides with RQ2, and will conclude my discussion on how to support researchers in doing science communication. The second gap, however, is going to require additional study. Although our design recommendations take a stab at solving the community discussion problem we've identified, there are other issues with how domain non-experts use scientific information online. In particular, I'll take a look at the case of more controversial scientific domains in Chapters 6 and 7.

Overall, by using qualitative and quantitative methods to study science communication from the perspectives of both researchers and audiences, I have surfaced insights about how the design of participatory web platforms affects the flow of science communication online. For the rest of this dissertation, I'll focus on how to improve that flow.

Chapter 5

Study 3: How Audience Analytics Support Science Communication on Twitter

5.1 Introduction

In Chapter 3, I discussed how social media platforms—despite their potential for science communication—could be difficult places for researchers to discuss their work. One major problem is their difficulty *understanding who their audience is*. This is problematic, because successful science communication and public scholarship often relies on tailoring based on the interests of one's audience (Luzón, 2013; Luong, et al, 2019), particularly when communicating with domain non-experts (Hutchins, 2020). Additionally, scholars may not be motivated to publicly discuss their work at all if they don't believe there is an audience for it.

In this chapter, I will discuss how we developed Ripple, a tool to help describe the different publics in a researcher's Twitter audience. I will describe the process of developing Ripple, how it worked, and the results of an evaluation showing how it (and other tools like it) could improve researchers' science communication efforts on platforms like Twitter; in particular, it helped researchers frame their work to diverse audiences, worked as a success metric, so researchers could better assess their science communication efforts, and helped researchers make more informed decisions about whether to use social media for science communication at all, making such public scholarship a more consentful process (Im, et al, 2021).

One important note before getting into the details: I intend for the insights gained from the process of developing Ripple (design requirements, coding scheme, empirical results on how researchers can use audience analytics for science communication, etc) to be the primary contribution of this chapter, rather than Ripple itself. Between the development of Ripple and this writing, free access to the Twitter API was deprecated, effectively ruining the utility of Ripple itself. That said, with the proliferation of new “public-oriented” micro-blogging platforms (e.g. BlueSky, Mastodon, Threads), I hope these designs can be replicated and extended to assist researchers in utilizing these and future participatory platforms for public engagement.

Additionally, I will note that we chose the HCI community as a use-case, for similar reasons as Chapter 3, and that we focused specifically on Twitter given the community's heavy use of it as a platform for science communication (again, see Chapter 3).

This chapter addresses **RQ2**: “How can we design tools to support science communication and public scholarship by researchers on the participatory web?”

5.2 Literature Review: Invisible Audiences on Social Media

People often have difficulty assessing who their audiences are on social media. For example, Facebook users systematically underestimate the number of people who actually read their posts (Bernstein, et al, 2013). The situation may be even more difficult to estimate on Twitter, where retweets and quote tweets can propagate posts across a complex network of different audiences, often leading to much larger and varied audiences than users might expect (Lotan, 2011). Indeed, users seem to deal with this diversity by imagining either very abstract audiences (e.g. "the general public") or specific, targeted sub-groups within their personal or professional circles (Litt & Hargittai, 2016). However, given constantly-evolving demographic trends on Twitter (Oktay, et al, 2014), and the added uncertainty of downstream users reached via retweets (Lotan, 2011), these imagined audiences may not line up with one's actual audience, which are often demographically and geographically complex (Stoltenberg, et al, 2021).

This is a key challenge for Twitter-based science communication, given the need to tailor research contributions to particular audiences (Luzón, 2013; Luong, et al, 2019). Within HCI, researchers need to juggle several different audiences, including other researchers who may build on one's work, practitioners who design and build systems that draw on HCI research (e.g. software engineers and designers), as well as various other publics who may find a given body of work relevant. Given that these groups have different relationships with research, sociotechnical expertise, and interests, understanding which of these publics are in one's audiences is a key step to effective science communication online.

5.3 Ripple

We built Ripple by following an iterative human-centered design (HCD) process (Gasson, 2003). We built a text classification model for HCI-relevant publics, developed an initial prototype and used it in an initial study to explore users' information needs. We then iterated on the design and conducted a user evaluation.

5.3.1. *A model to predict who is being reached*

We designed Ripple to help characterize the invisible audience on Twitter, with the aim of allowing researchers to better understand who their tweets are reaching, determine the success and potential of their outreach efforts, and frame their work more effectively. Our first step in building Ripple was to develop a method of automatically categorizing Twitter users into relevant groups for HCI outreach, to visualize this information at scale. For full details on model development, see Appendix B.

We collected training data from CHI 2019 authors with Twitter accounts we could identify ($n = 373$), and sampled both their followers and "downstream audience" (those reached via retweets) during April 2020, resulting in a sample of 11,694,199 unique Twitter users. Three authors and five research assistants openly coded batches of 50 randomly-sampled users from that set based on their profession, developed a closed codebook, and iterated on classifications until reaching sufficient inter-rater reliability (Hallgren, 2012; Krippendorff's $\alpha = 0.70$). We retained 4 categories overall: researchers (an important public for science communication; Burns, 2003), designers, software engineers (both important practitioner groups for HCI; Colluso, et al, 2019), and a catch-all "other" category, which we theorized as the "general public" (Burns, et al, 2003).

To allow our coded categories to guide our model, we used a semi-supervised topic modeling approach using correlation explanation (CorEx) (Ver Steeg & Galstyan, 2014) with anchor terms (Gallagher, et al, 2017). This allowed us to define topics and anchor terms to guide the model toward our categories (for a list of topics and associated anchor terms, see Table 7).

Category	Anchor terms
Researcher	prof, professor, science, research, researcher , lab, university, faculty, grad , masters, machine, data, phd
Designer	design, designer, ux, ui, user, experience, interface , prototype, sketch, figma, visual
Software developer	developer, software, code , app, mobile, programmer , frontend, backend, coder, ios , android, ml, game, engineering, engineer

Table 7. Anchor terms used to guide our semi-supervised topic modeling approach. Bolded terms are among the top 10 terms for that topic, based on the amount of explained variance.

We trained the model on a randomly sampled set of 100,000 user bios from our database (69,426 after removing non-English bios based on the langdetect package for Python). We then tested the model on our ground-truth set of 526 coded bios (see Table 8). Because past research in this domain did not provide sufficient metrics to fully gauge prediction accuracy (e.g. providing only false-positive rates, without measures of recall/sensitivity; Barthel, et al, 2015; Côté & Darling, 2018; Kopke, et al, 2019), it is difficult to compare our model's success against these methods, as they did not provide more complete measures like F1, balanced accuracy, or AUC. However, our approach performs as well or better than similar methods for classification of Twitter bios for related tasks (e.g. measuring political affiliation (Cohen & Ruths, 2013), profession, or personal attributes (Wagner, et al, 2013)).

Category	Precision	Recall	F1
Researcher	.96	.85	.90
Designer	.92	.91	.91
Software developer	.92	.74	.82
Other publics	.92	.97	.94

Table 8. Classification accuracy for Twitter user prediction model.

Case study of HCI researchers using our model. To illustrate the general trends and proportions of the categories in our model, I provide here a brief overview of the reach of the HCI community on Twitter. Running our classifier on our dataset of 373 HCI researchers' Twitter accounts, the median researcher in our sample had 597 followers, with 252 researchers, 62 designers, 40 software developers, and 248 among other publics. Figure 6 displays trends in the relative proportion of different audience types among HCI researchers with different follower counts. The general trend shows that smaller accounts tend to have a relatively high (50%) proportion of researchers following them, but that larger accounts tend to have more "other publics" and somewhat fewer researchers.

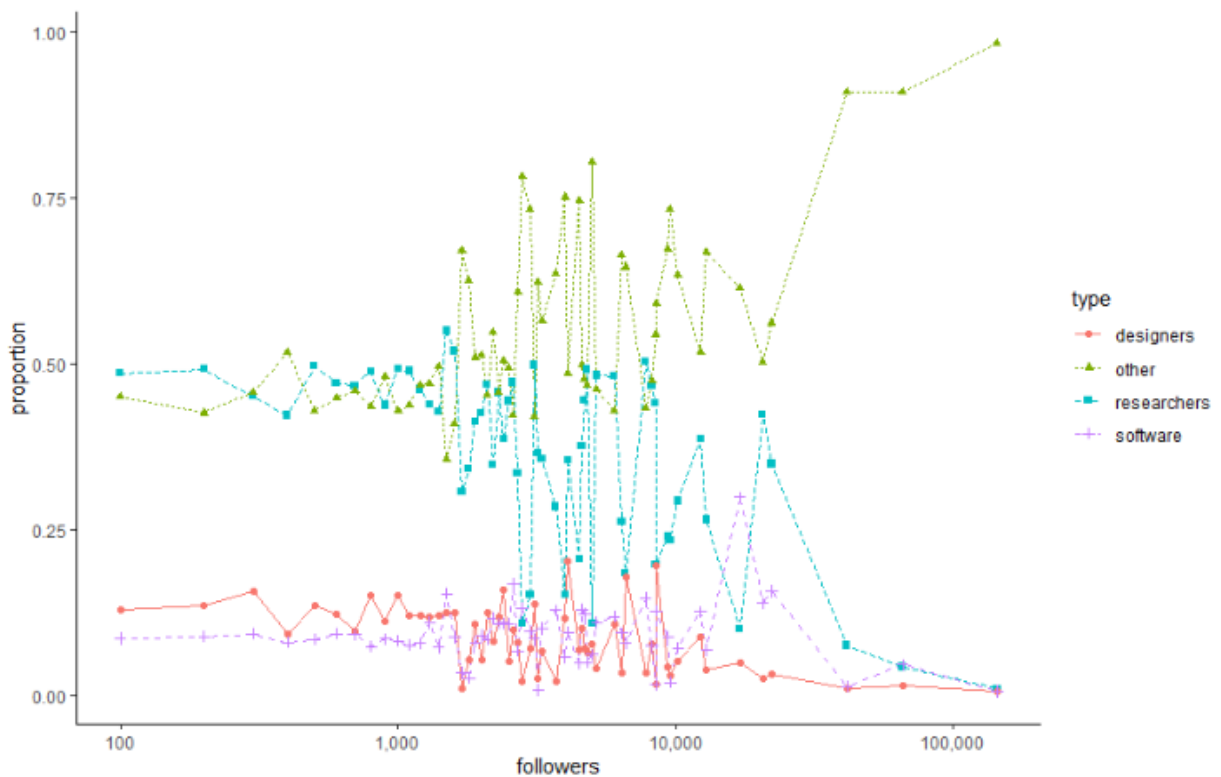


Figure 6. Proportion of different account types in CHI researchers' audiences, inferred using our model, by total follower count. For visual clarity, users are bucketed into average groups every 100 followers. Because accounts can have multiple classifications, proportions sum to greater than 1.0 in some cases.

5.3.2 *Initial prototype*

The initial prototype for Ripple included three main sections, each corresponding to increasingly specific levels of information (see Figure 7). At the top of the page, it displayed "**A Look at the HCI Research Community on Twitter**". This section displayed high-level information about the HCI community (defined as the set of CHI authors we sampled in 5.3.1). The second section, "**My Statistics**," displayed information about the user's individual data. It included information on the user's "downstream," which we defined as the followers of the users who retweeted them (i.e. those who would be potentially exposed to their tweets other than their own followers). By comparing the size and proportion across proximal and downstream followers, we hoped to highlight the size and diversity of researchers' invisible audiences, potentially inspiring them to rethink who their tweets may be reaching. The "**My Contributions**" box attached to it included information about how frequently they tweeted out links to papers and blogs (meant to roughly measure science communication behavior), and how many likes and retweets those tweets received. Finally, the "**My Tweets**" section displayed the downstream audience for their five most recent tweets with at least one retweet, to provide more granular information about the reach of specific tweets.

Our initial prototype used a simplified version of our model (only predicting researchers vs. non-researchers), and the information included was meant to showcase the capabilities of our system at a high level, while providing a space for participants of our iterative study to envision additional features, use cases, and stakeholders.

5.3.3 *Initial user study*

The goal of our first study was to identify what additional information HCI researchers would want from Ripple, and how the information provided in the prototype might already affect their approach to using Twitter. We recruited seven participants (see Table 9) by randomly sampling from three strata of our CHI 2019 sample; we bucketed our sample into those with fewer than 500 followers, those with between 500 and 5000 followers, and those with more than 5000 followers, then reached out to random samples from each of those buckets via email. We sent 49 emails in total, for a 14.3% response rate.

A look at the HCI Research Community on Twitter



Figure 7. Initial prototype for Ripple. Dots indicate additional tweets cut off by screenshot.

ID	Followers (at time of test)	Average tweets per month	Position
P1	400	9.6	PhD student
P2	500	7.3	Industry researcher
P3	600	35.5	PhD student
P4	2000	75.7	Full professor
P5	1000	24.9	Industry researcher
P6	300	4.8	Postdoctoral researcher
P7	5000	113.7	Assistant professor

Table 9. Demographics of initial user study. Follower counts are rounded to the nearest hundred (for <1000 followers) or nearest thousand (for >1000 followers) to protect participant anonymity. Academic ranks are listed using their North American equivalent.

Each session lasted approximately 1 hour. They began with an initial interview about the participant's habits and goals when using Twitter, followed by a think-aloud protocol where they were walked through the different sections of the tool and asked for their initial impressions, any surprising insights, how the information might change the way they engage with Twitter, and what additional information or features they would like to see. To ensure participants felt comfortable providing negative feedback as well as positive, they were instructed that this was only a prototype meant to get more information about their needs, and that any and all critique was welcome.

I conducted all the transcription, coding, and analysis. Analysis was done by starting with a deductive coding approach, with data sorted into broad categories based on "current utility" and "additional needs." This was followed by a process of memoing (Birks, et al, 2008) and thematic analysis (Braun & Clarke, 2012) to identify what insights participants were already receiving from their use of the prototype, as well as determining what additional information could be useful in helping them achieve their goals. Insights from this analysis process are presented below.

Insights gained from prototype. One feature participants found useful about our system was the ability to identify how many researchers vs. non-researchers were exposed to specific tweets, allowing them to use it as a kind of **success metric**. For example, P6 discussed how an advertisement for a workshop had less exposure to the research community than they expected:

What surprises me is that big decrease in the amount of researchers that actually might be interested in this. And I don't know if the hashtag is just not appropriate or maybe, you know, people who are in the HCI community are not that interested in this kind of field yet...(P6)

Another use was that learning more about their audience could prompt researchers to re-think their use of Twitter. On one hand, learning that they may be exposed to more non-researchers could prompt them to **frame their research more accessibly** to better engage those groups:

If you're not a researcher, you have no idea what any of this means. I think you have to be in HCI or NLP to make heads or tails of this. And upon reflection...if there was anyone who was a non researcher, who was like a real audience member, I would think maybe I should do this differently. Maybe I should make it a bit easier for someone who's not in this to get into it. (P3)

This may be especially important because several participants found they had more exposure to non-research audiences than they expected ("The thing that surprises me the most was that, I thought I was only interacting with the researchers, but no." ~P5). However, P2 found that they were exposed to more researchers in their downstream than they expected, which could prompt them to be more "cautious" about what the post in the future:

It makes me more self-aware, I guess. It might make me more cautious in the way I use Twitter, it might make me more likely to share research and work-related stuff...Because, as you're showing me here, potentially down the line, it could be picked up by other researchers. (P2)

Additional needs. However, participants also noted several additional features they might like to support them in using Twitter professionally. First, several participants expressed wanting more **granular information about their audience**. In particular, participants wanted to know more about practitioner groups relevant to their research, such as designers, software developers, and related groups in the technology sector (P1, P5, P7). One participant wanted this information to determine whether their work was being taken up by specific groups:

Because the stuff that HCI people do are so interdisciplinary, you want to know how it's being taken in by these fields. For example, if I used some NLP technique in my paper, I want to know how it's been taken in by an NLP researcher, but at the same time, I want to know if someone who's not an NLP person, like let's say a UX designer, if they will be able to just replicate what I have done, and be useful for whatever their job is. So that would be helpful, to see what kind of breakdown I have on the audience. (P5)

More granular insights might also be useful for researchers who use Twitter to recruit for studies:

We do occasionally use Twitter for recruiting participants, as a way of reaching some of these communities. So, knowing more about what the composition of the downstream audiences, or even what the composition of my followers is, would be helpful for understanding, and potentially planning, what kinds of groups we could reach for future studies. (P7)

Participants also wanted help **learning how to tweet effectively**. Even if one knows more about the audience, it might not necessarily be clear how to leverage that information into more engaging or useful tweets:

I realize I'm not very good at Twitter. Like, I'm having trouble even thinking about what operational decisions I have to make. It's like, it feels like my palette is limited, it's just phrasing and when I announce things. (P1)

Finally, there were a few features that were not considered very actionable. In general, the "Community" page highlighting community-wide trends, visualizations of follower growth and tweet engagement, and "My Contributions" block were considered interesting but not particularly useful by most participants ("A lot of this stuff is interesting in an infographic-y way, but I don't know what operational decisions I would make differently. I'm not really sure what conclusions to draw." ~P1). In addition, one participant felt they had no use for the prototype in its current form, feeling none of the information would be likely to affect their tweeting habits and suggesting this approach may not be useful to all researchers ("This isn't information that I've had a dying interest to know. And so that's why I'm not really sure how to process this." ~P2).

5.4 Final design

Our first study provided a number of helpful insights, which we incorporated into the final design. First, we found that information provided by our prototype already showed participants that their audiences may be larger and more diverse than they realized, affecting how they intend to use Twitter going forward. Moreover, we found that researchers need more information about their audiences than just their identity as a researcher or not, in order to more effectively engage them, assess whether they were reaching important stakeholders, and determine whether they could reach certain populations for things like study recruitment. They also needed more help leveraging information about their audience into more effective tweets. Based on these insights, we iterated on the design of Ripple, before conducting a larger evaluation.

Our first change was to remove the "Community," "My contributions," and follower/tweet growth sections at the top of the page, given their lack of utility for our participants. Instead, because our participants needed more granular information about their audience, we focused the following four updated sections on providing more specific and actionable audiences for HCI researchers on Twitter.

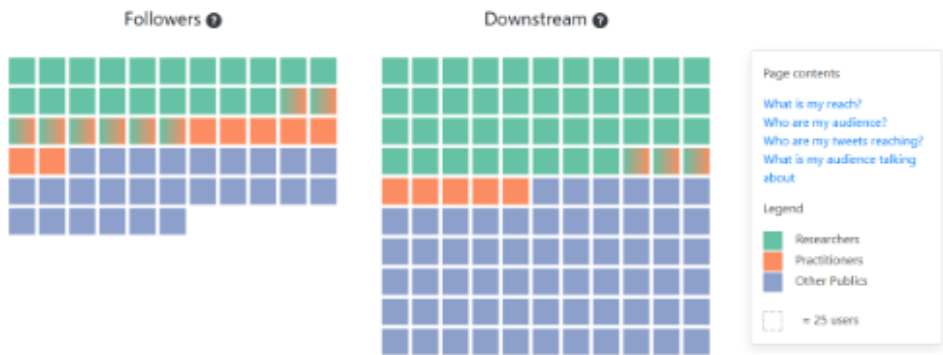
The first section in our final design was titled "**What is my reach?**" (see Figure 8). To provide finer-grained insights into users' audiences, we expanded to our full set of coded categories (see Section 5.2), pooling software developers and designers into a "practitioners" category. This was

primarily done to keep the number of categories low (and allow mixed icons without confusing the user), although future tools and models could consider breaking this down more deeply. This section is meant to provide an overview of the broad publics users are currently reaching, and to afford an immediate comparison between one's proximal followers and their downstream; because this distinction yielded some of the more surprising insights for participants in our first study, we chose to provide this information up-front. Gradients in the visualization refer to accounts dual-coded as researchers and practitioners.

Next, to provide more granular insights about users' audiences, we designed the "**Who are my Audience?**" section. Because Twitter users' bios tend to reveal significant information about their expertise and interests (Wagner, et al, 2012), we expected that simply aggregating frequently-used words from each section (researcher, practitioner, other publics) of one's followers and downstream would reveal useful information about who makes up one's audience. We used circle packing with a flat hierarchy, with the size of the circles representing the relative frequency of that term in that section of the audience. To ensure terms represented interesting topics, English stopwords were removed, and the first author iteratively removed an additional list of words that provided no topical information (e.g. "formerly", "like", "get") or that were already strongly associated with our topic models (e.g. "prof", "data", "research"; see Appendix C). Users can click each circle to bring up a random sample of users with that keyword in their bio, to see who they are and how the term is being used in context.

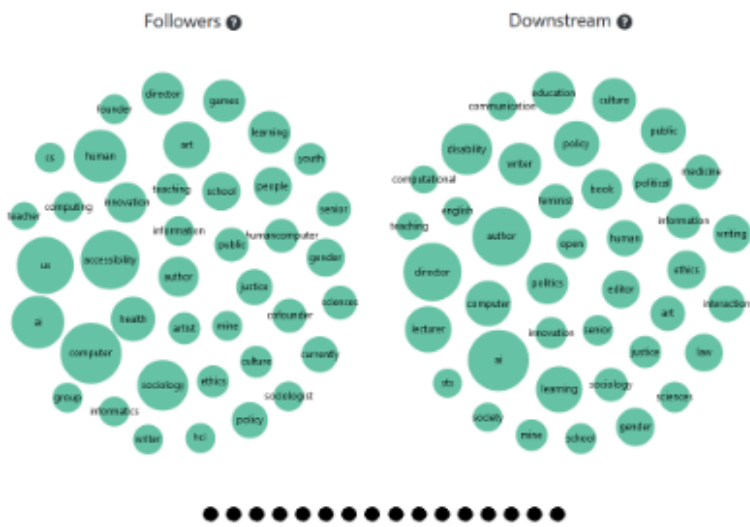
The third section, "**Who are my tweets reaching?**", is mostly unchanged from the prototype; however, to save space, we used an image carousel design rather than placing them directly on the page. In addition, to provide users with actionable information to improve the reach of their tweets, we include several research-backed tips in text above the tweet carousel. Several highlighted the importance of leveraging information about one's audience to write tweets with high information utility (see Appendix D for full tips).

What is my reach?



Who are my audience?

By looking at keywords from people's bios, we can learn more about how they identify themselves.



My Recent Tweets

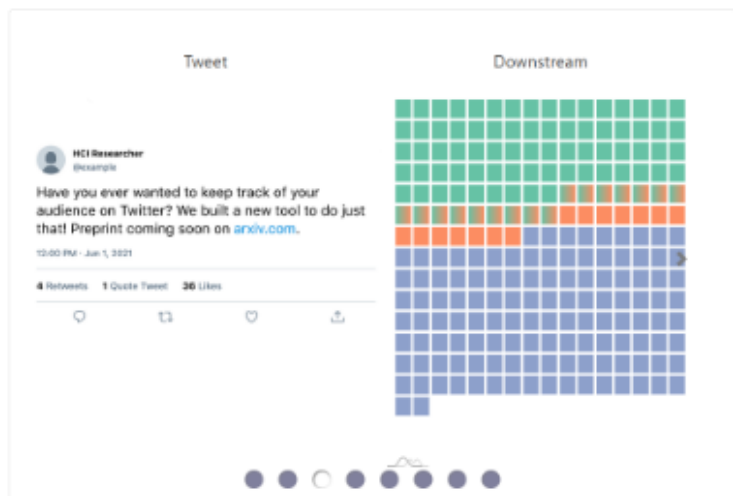


Figure 8. Overview of the first three visualizations in the final Ripple design.

The last section was titled "What is my audience talking about?", and contained two main segments meant to help identify what one's audience is currently discussing, and consequently, what their audience is interested in. First, users could read about "trending hashtags" from their audience (see Figure 9). To do this, Ripple randomly samples up to 1500 users from both their followers and the downstream for their previous 5 tweets with at least one retweet, and counts the hashtags used in this sample. It removes hashtags used by only one account, to help ensure these hashtags are actually being used by multiple members of the community. Users can click the hashtags to bring up a random sample of up to 20 tweets using that hashtag. This is followed by a segment providing the five most highly-retweeted tweets from the above sample of users, meant to provide more information about what tweets and topics are popular among one's audience.



Figure 9. The first part of "What is my audience talking about?" lists the most popular hashtags from the user's followers and recent downstream from the past week.

5.5 User evaluation

To determine whether our changes were successful, we ran a second user study. To reach out to a larger sample of HCI researchers with Twitter accounts, we advertised our study on multiple

universities' HCI-focused Slack channels, posted it on Twitter, and asked participants to refer contacts that might be interested. Our final sample (n = 25) included 16 PhD students, 5 professors, 3 industry researchers, and 1 undergraduate student. Their median follower count was 308.5 at the time of testing, with a range from 33 to 8031. For a full list of participants, see Table 10.

To explore how using Ripple might affect researchers' attitudes and behavioral intentions around public scholarship, participants were sent a short survey prior to each study asking "When you have a new paper published, how likely are you to tweet about it?", "How valuable do you think it is to tweet about your papers? Consider not just value to you, but to the broader public as well.", "How well do you think you know what your audience on Twitter is interested in?", and "How capable do you feel at framing your research in a way that interests your audience on Twitter?" All responses were made on 5-point Likert scales, anchored at 1 (not very likely/valuable/well/capable) and 5 (very likely/valuable/well/capable). This survey was given to the participants immediately after the session as well, as a pre-post measure.

During the study session, participants were first asked to write a tweet about a recent paper or project of theirs, and to talk through their strategies and considerations while doing so. They were then walked through the current version of Ripple, given the opportunity to explore their own data before being asked about their impressions, how the information presented affected their perception of their audience, as well as how that information might change their approach to Twitter in the future. After exploring the tool, they were then asked to write another tweet about the same paper, and asked how using Ripple affected their approach (if at all).

ID	Followers	Position	Region	Topic
P1	300	PhD Student	North America	Privacy and Security
P2	400	PhD Student	North America	Privacy and Security
P3	300	PhD Student	North America	AI
P4	200	PhD Student	North America	Accessibility
P5	200	PhD Student	North America	AI
P6	400	PhD Student	Europe	Interaction Techniques
P7	300	Undergraduate Student	Asia	Interaction Techniques
P8	1000	Industry Researcher	North America	Learning and Education
P9	200	PhD Student	North America	AI
P10	100	PhD Student	North America	Health
P11	500	PhD Student	North America	Critical Computing
P12	1000	PhD Student	North America	Accessibility
P13	100	PhD Student	North America	Computational Interaction
P14	200	PhD Student	North America	Visualization
P15	300	PhD Student	North America	Learning and Education
P16	100	PhD Student	North America	Understanding People
P17	3000	Professor	Europe	UX
P18	500	PhD Student	North America	Computational Interaction
P19	100	Industry Researcher	Asia	Interaction Techniques
P20	200	PhD Student	North America	Learning and Education
P21	6000	Assistant Professor	North America	Computational Interaction
P22	1000	Assistant Professor	North America	Critical Computing
P23	8000	Assistant Professor	North America	Data Science
P24	500	PhD Student	North America	Learning and Education
P25	2000	Assistant Professor	Europe	Games and Play

Table 10. Participant characteristics for user evaluation. Follower counts are rounded to the nearest hundred (for <1000 followers) or nearest thousand (for >1000 followers) to protect participant anonymity.

5.5.1 Analysis

For our final evaluation, we used a codebook thematic analysis approach (Braun & Clarke, 2021), supplementing an initial set of deductive codes by iteratively coding transcripts to generate new codes to capture surprising results. This led to a final codebook, containing 31 unique codes. Next, each transcript was coded based on this final set. This was followed by a standard process of thematic analysis (Braun & Clarke, 2012), which involved generating, reviewing, and refining themes related to the use cases participants identified for Ripple, their current and intended strategies for using Twitter, and any remaining challenges or additional considerations.

5.5.2 Results

In this section, we discuss how the information provided by Ripple leads to actionable insights about researchers' audiences on Twitter, prompting more targeted and accessible tweets to non-researcher stakeholders, tweeting about content their audience is likely to care about, making connections to new communities of research and practice, and helping researchers make more informed decisions about their Twitter activity. Quotes are lightly edited for clarity.

Revealing the invisible audience prompts more considerations of accessibility. By revealing the overall breakdown, frequency of keywords, and size of the downstream, Ripple provided participants with many surprising insights about their audiences, such as their size ("I think the most important takeaway for me is that there are definitely more people than you realize that view your tweets." ~P11), relative number of non-researchers ("I'm again surprised seeing the larger number of other publics." ~P2), their members' interests ("Some of these keywords, like accessibility, AI, computational, they have nothing to do with my research." ~P1), or the presence of specific groups ("So it looks like I've got the disabled community in there too." ~P5). After seeing that they had more access to publics outside of academia than they realized, some participants intended to frame their tweets to target them specifically, especially when they felt their research might have value for specific groups:

After seeing this, I think I will write a separate thread for practitioners. Most of the time, my audience is mostly focused on researchers, although I want the

impact to reach practitioners. I think the first tweet is kind of too focused on academics. So I think I might actually write a separate thread. This version is for practitioners, like, well, what's the TLDR for designers or developers? Like, they are less interested in the numbers, they are actually more interested in, so what, what should we do? (P11)

To do this effectively, participants committed to using appropriate language and framing devices for the particular stakeholder groups they realized they had access to:

From the analysis that we did in this session, I realized that most of my audience is in the general public category and among those audiences, there are a lot of people who are somewhat related to the domain of accessibility and disability. So what I've done here is that I've kind of focused on that and I've used their language a little bit more specific to that. (P12)

Furthermore, because seeing the downstream revealed a much larger audience than many participants expected, it could also prompt researchers to tweet more in general:

I guess it makes me more confident about tweeting out. I think my strategy would have been, it's okay even if you're tweeting into a black hole, just tweet. But I guess now it makes me think, no, I can get a decent reach, so I should still try to reach out. (P9)

These findings are echoed by our survey results, where participants responded that they were significantly more likely to tweet about their papers in the future (pre mean = 4.50, post mean = 4.84, $t(24) = 2.81$, $p = .010$, $d = 0.55$), and that they thought that tweeting about their papers was significantly more valuable (pre mean = 4.15, post mean = 4.54, $t(24) = 3.08$, $p = .005$, $d = 0.60$), after using Ripple.

Audience insights led to reflection on reach. By learning more about what audiences were exposed to their work, participants were able to evaluate if they were meeting their goals on Twitter, and plan to adjust their behavior accordingly. This could include adapting one's tweet content, the framing of those tweets, or the communities they connect with ("I think this is a very interesting tool for me to sensemake about my tweets, and even explore who to follow" ~P3). In some cases, participants may realize they aren't reaching communities they thought they were, and decide to tweet more about certain topics:

Not a lot of privacy peeps. So I think that maybe I need to be more active in that area, like talking about those. So I can reach more people who study that. (P1)

In other cases, seeing the particular downstream audiences for a given tweet can help reverse-engineer successful strategies. For example, tagging co-authors or relevant accounts:

I guess I just wasn't aware of who the audience of the people I was tagging have, and it's kind of given me that idea as well. So I guess if I want more audience, I'll tag the right people in it. (P6)

Beyond structural elements like tags and hashtags, others decided it would be useful to frame their work to highlight its relevance to either existing members of their audience, or communities they wished were following them but weren't:

If I want to exploit the current interests of my audience, I'm going to rewrite this to focus on data science, ML approaches like evaluation of curriculum, but focusing on the data science methods part of it. If I want to try to get new audience members that are more aligned to my current work, then I would try to use other keywords like education research. (P8)

Again, these results are in-line with our quantitative findings, as participants responded that they felt like they knew their audience's interests better (pre mean = 3.27, post mean = 3.92, $t(24) = 3.05$, $p = .005$, $d = .60$), and that they felt more capable at framing their research to fit their

audience's interests (pre mean = 3.11, post mean = 3.92, $t(24) = 4.60$, $p < .001$, $d = .90$), after using Ripple.

Visually organizing communities helps junior scholars navigate Twitter. Several participants discussed how the "Who are my Audience?" section of Ripple was particularly useful for identifying communities our participants wanted to connect with. This functionality could be especially useful as an onboarding tool for junior scholars, particularly those who do not have many prior connections with HCI Twitter:

I think a lot of people, especially from the Global South, they don't have a lot of connections with people who are influential in HCI, you know? So, if they have to reach out to someone, probably Twitter could be one of the mediums to do that. They could actually immerse themselves and know what's going on in HCI. So, I think your tool could actually help a lot of researchers in the Global South know what is something they could actually do better to communicate with people in HCI. (P7)

More established scholars and/or those with larger twitter audience may no longer need this functionality, however, as their audience is broad enough that they have adequate reach into the communities they care about, and they may have developed intuitions for what communities are present on Twitter already ("Having spent a lot of time on Twitter, I feel like I implicitly know a bunch of the things that this interface is kind of telling me, whereas for someone who doesn't spend as much time on Twitter, they like might learn more from such an interface" ~P21)

Revealing who is exposed to one's work provides agency over one's Twitter presence. Finally, some participants noted that seeing who was exposed to their tweets gave a sense of "agency" (P11) or "autonomy" (P10) over their data. As P11 put it:

The system kind of gives users access to their data, in some sense. It lets users view what the data of their audience is actually like. And to me, being able to know that is pretty powerful. I think the system makes it more transparent about,

oh, this is your audience. So it lets users make informed decisions about what to tweet.

As we previously found in Study 1, exposure to unexpected audiences can cause researchers to be more careful about what they tweet about. P15 illustrates one such experience when viewing their audience's keywords:

For the downstream, it's like reaching the other side of the internet. They're like, you know, like [religious and political groups]. I didn't even know that my tweet could be seen by those people. And, I'm not sure how that will impact the things I tweet...I obviously don't want to start like a fight on my Twitter account, so maybe I won't tweet controversial stuff or sensitive information.

Changes to tweet style based on audience insights. Using the codebook as a guide, participants' tweets before and after using Ripple were coded based on the presence of hashtags, tags, technical jargon, and images, their tone, their use of "hooks," and what issues they used to frame their work (See Table 11 for the total counts for each strategy in our sample). Several participants used additional hashtags in their second tweet, often with the intention of targeting specific communities they noticed in their data ("I would use more hashtags for sure, when I'm mentioning those keywords like "accessibility"... it might help me reach more people." ~P4). Participants also tagged more users, realizing how large their potential downstream audiences might become ("It's made me more aware that when someone's tagged in the tweet, there is a bigger audience." ~P6).

Beyond adding these broadcasting features, other participants chose to reduce the amount of jargon in the second tweet, add a hook at the beginning to attract interest from more general audiences, or frame their work to highlight its importance for a particular group in their audience. To preserve participants' anonymity, we altered one set of pre-post tweets using a phony research topic to exemplify the changes participants typically made (Figure 10).

Strategy	Count
Changed framing	12 (48%)
Added hashtags	8 (32%)
Added tags	5 (20%)
Reduced jargon	5 (20%)
Added a hook	2 (5%)
Added an image	1 (2.5%)

Table 11. Number of participants who made various changes to their tweets after seeing Ripple

Pre:



Post:

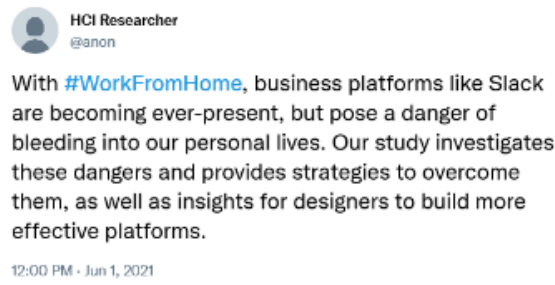


Figure 10. Example tweets generated to reflect typical changes in our participants’ tweets before and after using Ripple, including addition of hashtags, reduced jargon, hooking into a popular topic in the first sentence, and highlighting the relevance of a specific practitioner community.

In this case, the participant wrote a hook related to an ongoing popular topic, specifically discussed their work's relevance to designers, and reduced their technical jargon. Many participants also added hashtags, which the example tweet also reflects.

5.6 Discussion

In Chapter 3, I described a set of challenges that researchers have when using the participatory web for science communication. Namely, they do not know who their audience is on social media. This posed two main barriers: An inability to properly frame one's work in order to match their audience, and a lack of insight into whether their outreach is successful. In this chapter, I show that an audience analytics tool has the potential to solve both of these problems; participants who used Ripple learned more about their audience on Twitter, used that information to reflect on how to more properly frame their work to invite in other publics, and to determine whether they were reaching the groups they wanted to reach. This answers RQ2, describing the potential for technology solutions to support science communication on the participatory web.

Tools like Ripple may also help address other challenges for academic twitter, as researchers (particularly those from underrepresented populations) may be vulnerable to backlash and harassment, a significant challenge for those without experience navigating these networks (Stewart 2016). Recent work has generated numerous design features stemming from notions of affirmative consent (Im, et al, 2021). By unveiling who researchers are actually exposed to downstream, as well as what topics are being discussed among their audience, Ripple provides features of an "informed" design (i.e. one that provides users with necessary information about their interactions with a social platform, in this case which stakeholders may be exposed to their work). These features may assist those new to Twitter in navigating the various modes of discourse across different Twitter communities (Stewart, 2016), and better understand the potential consequences of their interactions on Twitter before deciding whether to tweet about a given paper, or even use the platform at all.

Finally, such tools can help establish the impact and importance of science communication on Twitter, and social media more broadly. With past research suggesting that most researchers are followed primarily by other researchers (Côté & Darling, 2018), our approach of visualizing downstream audiences can help individuals see who may have actually been exposed to a given research paper, with those downstream audiences often including far more non-researchers. Moreover, given that calls have been made for academic departments to consider science communication as an integral part of academics' responsibilities and consider them for tenure

promotion (McCall, et al, 2016), this use of Ripple as a success metric could help highlight the potential impact of Twitter-based scholarship. Similar to altmetrics (Sud & Thelwall, 2014), audience analytics tools could help empower researchers to signal the impact of their work, and potentially provide incentives to communicate to other important stakeholders outside of academia.

5.6.1 Future work

With Ripple as a use case, I have answered RQ2, showing the potential impact such tools can have on science communication via the participatory web. However, additional research is likely required in order to make the most of this potential. Although not a focus of the rest of this dissertation, I want to highlight some important considerations for expanding on the work outlined here.

Improved tools to write research-based tweets. Although the information Ripple provides was considered useful by our participants when crafting research tweets tailored to their audiences, it may not always be easy to put those insights into practice. One solution may be to provide framing suggestions---and previously identified linguistic strategies for science communication and tweets---automatically via NLP-driven suggestions. For example, recent work shows that common science communication strategies can be predicted from text (August, et al, 2020b), which could potentially allow for just-in-time interventions and make suggestions for users writing tweets about their research. This technique could be integrated with individualized data for each user, suggesting science communication strategies shown to work for different audiences types (Davis & Russ, 2015; Yang & Hobbs, 2020), as well as Twitter-specific suggestions for more effective tweets (Tan, et al, 2014; Kopke, et al, 2019). Formalizing actionable suggestions this way could reduce the barrier between seeing one's data through tools like Ripple and actually producing more effective tweets, which may be especially useful given how little time most academics have for things like science communication and public scholarship (Vostal, 2015).

Generalizing to other research communities. I have demonstrated that Ripple can be an effective tool for HCI researchers, but more work can be done to extend it to other research communities.

Every field has its own particular considerations for science communication (Gerber, et al, 2020), so additional work identifying their relevant practitioner communities and other stakeholders would allow the methods behind Ripple to serve other research communities' needs on Twitter as well. This would likely require more in-depth study of the particular challenges, goals, and circumstances of the fields in question, given the extreme diversity in how social media is used to discuss research across fields (Holmberg & Thelwall, 2014). However, the ability to visualize the relevant features of one's audience is likely relevant to most researchers on Twitter, both to frame their work more effectively, and to make informed decisions about whether to discuss their work online at all.

Generalizing to other online platforms. Additionally, although Twitter has historically been an important platform for science communication in HCI (see Chapter 3), changes in platform ownership and governance have reduced some researchers' confidence in its long term viability, prompting them to consider alternative platforms like Mastodon (Stokel-Walker, 2022). A similar approach could be used to develop analytics tools for such alternative platforms, or even to help researchers compare reach to different publics across platforms, to help determine the suitability of different online spaces for their particular science communication goals.

5.6.2 *Beyond HCI*

Chapters 3 and 5 have focused primarily on the HCI community as a testbed for my questions around science communication on the participatory web. I would argue there were several advantages to doing this, given its applied nature, focus on sociotechnical systems, and diversity of research questions, methods, and stakeholders. These factors were helpful in thinking through questions of audience types, targeting, framing different contributions, etc. However, although science communication in HCI is an important endeavor for the reasons outlined above, shortly after conducting the first three studies in this dissertation, the world was faced with another science communication challenge of critical importance: the COVID-19 pandemic.

So, while the first three studies established strategies for connecting researchers with domain non-experts, generating insights about the communicators, their platforms, and their audiences, the last leg of my dissertation will turn to how to support online science communication with

more skeptical (and sometimes adversarial) audiences. How do the needs of an apprehensive public differ from the publics examined so far, and how can we communicate controversial scientific information leveraging participatory web technology? Chapters 6 and 7 will examine these questions.

Chapter 6

Study 4: The Design of COVID-19 Vaccine Meta-Summaries

6.1 Introduction

In March 2020, the World Health Organization (WHO) declared the COVID-19 outbreak a pandemic (WHO, 2023). Contemporary readers likely need no introduction into the particulars of the pandemic, given its years-long global impact on virtually all facets of life. However, one important dynamic was that—despite their availability in early 2021—a large number of people chose not to get the vaccine, leading to an excess of preventable hospitalizations and deaths (Cuadros, et al, 2022).

Concerns about vaccine safety and misinformation have played a large role in vaccine hesitancy (Sgaier, 2021), so communicating about vaccine research responsibly and effectively is an important challenge. In general, highlighting scientific consensus can help improve people’s beliefs about that topic (Van der Linden, et al, 2019), but some have argued merely citing the number of experts who agree with a claim is the wrong unit of evidence, and that communication efforts should focus on more direct evidence of consensus-building (Landrum & Slater, 2020). Moreover, perhaps because of the important role reactance plays in COVID-19 vaccine refusal (see e.g. Lu & Sun, 2022), recent work has recommended providing facts over explicit requests to get vaccinated, and approaching vaccine hesitant groups with empathy (Palmedo, et al, 2021).

To meet this need and communicate much-needed vaccine information, this chapter covers Study 4 in my dissertation. I report on online, interactive meta-summaries of COVID-19 vaccine safety research aimed at increasing public awareness, knowledge, and understanding in a transparent and trustworthy way. In study 4a, we conducted co-design interviews with vaccine hesitant people, in order to determine design requirements for vaccine communication. In study 4b, we developed and tested the above-referenced meta-summaries, comparing their efficacy to CDC communication about the vaccines at the time. In this chapter, I will demonstrate how this approach was successful at raising awareness and understanding of COVID-19 vaccine safety research among skeptical audiences, and discuss the potential for this meta-summary approach for controversial scientific topics.

This chapter addresses **RQ3**: “How can providing meta-scientific summaries of research questions help improve people’s awareness of, opinions on, and understanding research on the participatory web?” Parts of this chapter have been previously published (Williams, et al, 2022b).

6.2 Related work: Vaccine communication online

Recent work has examined the potential of various online interventions to inform the public about vaccines. These online interventions for vaccine safety communication have shown some promise at informing the public through videos (Salmon, et al, 2019), tailored information (Bennet, et al, 2015), and interactions on social media (Daley, et al, 2018). They may focus on providing information for “fence-sitters” who seek to make informed decisions about vaccination (Finnegan, et al, 2018), so providing clear, high-quality, credible resources is key. These online interventions represent a scalable approach to increasing public awareness and understanding of vaccine safety information, and given how difficult it can be for even experts to stay informed about rapidly evolving research fields like those related to COVID-19 (do Nascimento, et al, 2021), this scalability is important. However, existing public health websites on COVID-19 (Valizadeh-Haghi, et al, 2021), as well as other vaccine technology (Vivion, et al, 2020), can be difficult to read, or fail to utilize data and graphics effectively, suggesting more work should be done to build online interventions grounded in the information and design needs of vaccine-hesitant groups.

Another approach to improving vaccine attitudes is to communicate the degree of scientific consensus among medical researchers (Van Der Linden, 2015). While there is a large body of work showing that perceived scientific consensus can improve attitudes toward relevant scientific issues (Van Der Linden, et al, 2015a; Van Der Linden, et al, 2015b; Chinn, et al, 2018), some have argued that these consensus messages may not be using an appropriate unit of analysis (Landrum & Slater, 2020). That is, these past consensus messages have focused on whether individual scientists agree with a particular finding (e.g., “vaccines are safe”); however, such an authoritative message may induce backfire effects (Hart & Nisbet, 2012), and future consensus messages should highlight the process of consensus formation as agreement based on a given body of evidence. A more transparent approach may be more convincing, especially to

the rising number of people who distrust scientific institutions in the U.S. (Hamilton & Safford, 2021), as they are unlikely to defer to such appeals to authority.

To that end, we sought to develop ways of communicating COVID-19 vaccine safety research that highlights scientific consensus by summarizing direct evidence.

6.3 Study 4a: Designing for the Vaccine-Hesitant

6.3.1 Methods

Co-design is a research method where participants are asked to engage directly in the design process (Burkett, 2012). In our sessions, we asked them to sketch designs for a research summary that would best meet their needs. By framing interview sessions as a way of eliciting feedback to produce tools for our participants, we sought to establish a co-operative relationship and build empathy (Yuan & Dong, 2014). We expected this would help participants be more candid with their opinions and needs, particularly when working with a population with lower-than-average trust of science (see e.g. Doherty, et al, 2021).

To recruit participants, we deployed a screener survey on MTurk (n = 676), where we asked “Are you—or at some point were you—hesitant to get the COVID-19 vaccine (for example, Pfizer, Moderna, Johnson & Johnson)?”, “If you could ask any question about the COVID-19 vaccines (for example, Pfizer, Moderna, Johnson & Johnson), what would you ask?”, and demographic questions. We emailed those who responded that they were either currently hesitant, or at some point were hesitant, to get the vaccine, and indicated their willingness to participate in an interview. In total we reached out to 153 participants for a final sample of 22 who agreed to participate (14.4%). See Table 12 for full participant demographics .

ID	Gender	Race	Age	Education	Political Ideology
P1	Female	White	57	Bachelor's degree	2. Somewhat conservative
P2	Female	White	31	Master's degree	4. Somewhat liberal
P3	Female	Black	33	Master's degree	5. Very liberal
P4	Male	Black	28	Bachelor's degree	2. Somewhat conservative
P5	Female	White	38	Bachelor's degree	5. Very liberal
P6	Female	Black	29	Bachelor's degree	4. Somewhat liberal
P7	Male	White	31	Bachelor's degree	5. Very liberal
P8	Female	White	42	Associate's degree	2. Somewhat conservative
P9	Male	Asian	26	High school	3. Neutral
P10	Male	White	37	Master's degree	2. Somewhat conservative
P11	Male	Black	29	High school	4. Somewhat liberal
P12	Female	White	55	Associate's degree	4. Somewhat liberal
P13	Male	Black	34	Bachelor's degree	4. Somewhat liberal
P14	Female	White	33	High school	5. Very liberal
P15	Male	Black	40	Master's degree	1. Very conservative
P16	Female	Asian	42	Bachelor's degree	3. Neutral
P17	Male	Black	35	Associate's degree	4. Somewhat liberal
P18	Female	White	48	Bachelor's degree	2. Somewhat conservative
P19	Male	White	22	Associate's degree	4. Somewhat liberal
P20	Male	White	38	High school	4. Somewhat liberal
P21	Male	White	37	Bachelor's degree	3. Neutral
P22	Female	White	53	Bachelor's degree	4. Somewhat liberal

Table 12. Participant demographics for co-design interviews. Political ideology was measured on a 5-point scale (1 = Very conservative, 5 = Very liberal).

Our full interview protocol is provided in Appendix E. We began by asking preliminary questions about where participants get information about COVID-19 and vaccines, and what

made them hesitant. We then provided a list of information about scientific research (information about studies, their findings, their authors, institutions, funding sources, participants, etc), and asked what they might find useful when making vaccination decisions. We then showed off three mockups: a text-based summary of relevant literature, an interactive scatter plot, and a tool to simulate and visualize possible outcomes of getting vaccinated. We asked what was (not) useful about these mockups, and how they could be improved. We then asked how these might be implemented into social media or search engines, before ending by asking them to sketch a version of the tool that would be best suited to their needs. Sessions were approximately 45-60 minutes.

Interview data was analyzed using a thematic analysis approach (Braun & Clarke, 2012). We first transcribed the audio for each interview, open coded the first five to develop a coding scheme, then close coded the full set. Each coded section from each interview was added to a single document under that code, where we extracted high-level summaries of each code. These were then combined to develop a number of themes, with particular focus on the information needs and goals of different participants.

6.3.2 Results

Challenges using scientific papers. First, we found that scientific evidence was generally considered important, with several participants using research papers to help make decisions (“I had actually read a lot of scientific journals. I mean, I really dug deep into stuff like that.” ~P22). However, these papers were typically not perceived as useful as information sources. First, they were difficult to access (“A lot of the times they're behind paywalls and it takes extra time to actually get the content” ~P13). Second, even if they could be accessed, they were difficult to understand (“I didn't really read the raw science because it's way over my head.” ~ P20). Third, it can be difficult for non-experts to extract key takeaways, with multiple participants describing them as “boring” (“They're just kind of boring and I just want some basic information, like I don't really care to go in depth and that's what most of them are. I can understand what it's saying, but I just don't want to apply myself to do that.”).

However, our participants were interested in understanding the state of the research. Rather than searching through research papers, our prototypes that summarized key statistics and other information from the literature were considered useful. As P10 described:

This would help somebody like me, that's kind of on the verge of not knowing like, wanting to do what's best for everybody to help make a more informed decision without having to spend like 52 hours trying to source information, right? Going down the rabbit hole, and then being able to write it down or put it on a doc and okay, this says this and this, this, and it's like right here. You made the doc.

Given the need for a summary of relevant metascientific information in making vaccination decisions, we then analyzed what specific pieces of information participants considered useful, and how they would want it displayed.

Quantity and consistency of research results. First, many of our participants were convinced by data showing how much research has been done on vaccine safety, and how consistently safe the COVID vaccines have been shown to be (“Something like 8.8 million people kind of makes me more comfortable to go take the vaccine.” ~P16). Beyond the quantity, consistency was also important, with participants wanting to know results held over repeated studies (“I mean, if just one person does an experiment, that doesn't really prove much till it's like tested over and over again. So I think that part's really important.” ~P14). Others had specific needs, such as who the participants of the studies were (“If I see that more severe side effects are happening more in women, I probably wouldn't get it.” ~P8), depending on their specific questions.

Indicators of Trust. Not all participants were willing to trust that the data displayed was accurate. A common concern was that safety research (or how we were presenting it) was biased, so metascientific factors like funding source or institution were considered important (“let's just say Johnson and Johnson did the study, or that Moderna did the study. And I'm like, well, that's not unbiased.” ~P10). This was considered the most important piece of information by several participants, specifically those who lacked trust in scientific institutions (“Funding source, it tells

of a certain bias, I guess, for what they're looking for in their studies and whatnot, and who's funding them, who's giving them money, who made it possible. I think for me, that would be the most important for credibility.” ~P9). Information on what country a study was conducted in was also considered relevant, for those who believed research done in the U.S. is untrustworthy (“I would look at studies from different countries, yeah.” ~P1). Those who looked for this type of information expressed wanting to know the intentions behind the research; are researchers beholden to moneyed interests? Or are they doing research for altruistic reasons? Can they be trusted?

Design considerations. In terms of design, participants were split on how they wanted to engage with the research. For some, having the ability to interact with and interrogate the data was useful, either to determine its credibility or its relevance to their own circumstances (“I like to have a lot of numbers. That way I can analyze it myself, figure things out. [...] It's just the right amount of controllability. I can go from studies that have a hundred participants or studies that have a million, then hover over the icon and get even more of a breakdown of the information. So I think that's pretty amazing.” ~P17”). Others had no interest in this level of interrogation, preferring a clear message explaining key takeaways (“Interaction feels like a waste of time, especially when it's a message that could still be conveyed with a simple, still graphic that's already sort of developed for me. I just want a clear, clean, simple presentation of information that I can really just digest at a glance.” ~P20).

This difference also emerged explicitly in many of our participants' sketches. While there was some variety in form and function, most commonly participants generated two-tiered, interactive infographics. They often began with high-level, plain-language, bulleted summaries of the state of the research, to ensure the key takeaways are clear. This was usually supplemented by an interactive graph or other visualization, providing additional details on demand for those who want to more deeply interrogate the research. These often involved hovering/clicking on studies to propagate details like funding source, sample size, study population, etc. This general approach allowed for easy interpretation from participants who had no interest in exploring the details of the literature (“Hey, I'm just asking this one question. I just want one sentence really. And then if I'm interested by the answer, I'll click read more. Cause otherwise...this is just too

much or overwhelming and I'll just close out of it.” ~P19). For others, however, providing transparent details on the metascientific information (institutions, authors, funding sources) could improve trust, and help users make more nuanced decisions about the literature.

Finally, some participants were concerned about bias in the system. For some, the explicit narrative provided by some of our prototypes (e.g. one providing a text-based summary) could feel it's leading readers to a specific conclusion, and glossing over conflicting information, as P4 describes:

I feel like there would be some sort of study that maybe majority might lead to like this direction, but I'm sure there is some research out there, maybe like a very minute number, that might have opposite results than what's presented here. I would say having that as well might make the reader feel that they're the ones making the decision versus, you know, leading them to a certain decision.

To address this, visualizations that clearly display the full range of studies on vaccine safety could be considered more transparent, and less biased (“The bias was really just coming from how the information is structured or worded. [...] But with this [a scatter plot graphing all studies in our sample] you can look at each thing one at a time, so it doesn't feel biased anymore.” ~P19). Such an approach would likely rely on users' trust that the displayed range of studies is representative of the full literature.

Based on the findings from these co-design sessions, we generated a list of design requirements for scientific meta-summaries in this domain:

1. Provide simple, concise, text-based summaries of the information
2. Provide interactions for details-on-demand, to provide deeper insights for those who want to interrogate the literature and ensure credibility
3. Visually convey the quantity of research
4. Visually convey the consistency of research
5. Provide key metascientific signals of credibility (e.g. funding source)

6. Signal that the research displayed is representative of the full body of COVID-19 vaccine safety research

6.4 A Meta-Summary of COVID-19 Vaccine Safety Research

Based on the above insights and following our design requirements, we designed an interactive meta-summary meant to provide metascientific information our participants considered valuable when assessing vaccine safety research, in a format that would be useful to them. Following the formatting conventions participants used (high-level takeaways, details on demand), we designed four visualizations describing key pieces of information based on the needs we identified (see Figure 11).

We developed and tested two versions of our intervention. In general, our co-design participants were concerned about safety, they considered a large amount of consistent research to be useful in assessing safety, and they considered funding source to be useful in determining credibility. Our interventions prioritized signaling this information. In the first version (“safety only”), we first included visualizations about the number of participants across studies in our sample, using tick marks (e.g. “Population of Australia (40+ million)”) to contextualize the combined size of the studies in our sample. We next included study estimates of vaccine safety risk over time in a scatter plot (highlighting the consistent low risk estimates), where participants could click each study for additional details (providing a transparent overview of the research space). We specifically used serious adverse events as outcomes, defined by the studies on COVID vaccines in our sample, which included outcomes like myocarditis, anaphylaxis, and GBS. Finally, we included a graph of the frequency of different funding sources, which highlighted that most studies were funded by their own university or non-profit organizations.

In the second version (“full version”), we also included a graph depicting the efficacy of the mRNA vaccines at preventing serious outcomes, in order to additionally address the belief shared by a subset of our participants that the vaccine was ineffective or unnecessary.

For both versions, we also drew on qualitative work that suggests providing “facts over exhortations” for vaccine-hesitant people (Palmedo, et al, 2021). This is in-line with research on psychological reactance (Rosenberg & Siegel, 2018), whereby people respond negatively when they perceive that their freedom is being threatened. To address this, we adapted an “inoculation” message from past work (Richards, et al, 2021) to remind participants that they are free to use the information however they wish:

You’ve probably heard a lot of messages telling you about COVID-19 vaccines. Of course, you can decide what to do with those messages. We, a group of researchers at the University of Washington, have collected all published papers we could identify by searching for “covid,” “vaccine,” “side-effects, and “adverse reactions” on Google Scholar up to December 2021, and it’s up to you to decide how to use this summary.

6.5 Study 4b: Experimental evaluation

6.5.1 Methods

To test whether our interventions improved vaccine hesitant people’s awareness, opinion, and trust of vaccine safety research, and their intention to get vaccinated, we conducted a pre-registered (https://aspredicted.org/blind.php?x=56W_KT2) experiment on MTurk. There were three conditions: the safety only version, the full version, and a baseline condition where we included information from the U.S. Center for Disease Control’s (CDC) page on vaccine safety data.

Distribution. We deployed an experimental survey on MTurk. Participants were only allowed to take the survey if they were on a laptop or desktop computer, with mobile users being automatically removed, to ensure our prototypes displayed correctly. It was posted to MTurk with the title “Read about Covid-19 vaccines and answer a survey [CANNOT USE MOBILE]”, the description “Read some information about Covid-19 vaccine safety research and give us your opinions. [Mobile responses not allowed; must use laptop or desktop computer]”, and was tagged with the keywords “survey”, “research”, “vaccine”, and “covid.”

Conditions. Participants were randomly assigned into one of three conditions: the full version, the safety only version, and a baseline using information from the then-current CDC page on vaccine safety (see Figure 12). We chose this as a baseline because, like our interventions, it serves as a high-level overview of safety data on COVID-19 vaccines. It mirrors our intervention in that it provides the amount of research (“More than 520 million doses...”) and safety estimate (“VAERS received 11,225 reports of death (0.0022%)...”) Thus, it represents a then-current standard in how this information is being communicated to a U.S. audience by an official government body. Any improvement we show relative to this baseline represents an improvement on current communication with similar goals.

Measures. We measured vaccination status by asking “Have you been vaccinated for COVID-19?” and for those who responded “yes”, “Have you received a COVID-19 vaccine booster?” Vaccine intention was measured by asking participants “How would you describe your intention to get [next dose]?” (definitely/not sure/definitely not). Participants were also asked to their vaccine hesitancy concerns on a 5-point likert scale (“I am not worried about getting infected with COVID-19”, “I do not believe the COVID-19 vaccines are effective”, “I do not believe the COVID-19 vaccines are safe”, “It is too costly to get a vaccine (for example, can’t get transportation, can’t take time off work)”).

We measured credibility of US vaccine research using three subdomains from prior work: trustworthiness, competence, and benevolence (Jensen & Hurley, 2012). Specifically, they were asked to rate their agreement with the following statements on a 5-point scale: “I think COVID-19 vaccine safety research in the United States [is trustworthy/is competent/protects public interest].” We also measured their trust of the information in the meta-summary itself, using agreement with two statements from prior work (“I think the information I just read was [believable/balanced]” on a 5-point scale (Yale, et al, 2015).

What You Need to Know About COVID-19 Vaccine Safety

COVID-19 vaccines are safe and effective.

Millions of people in the United States have received COVID-19 vaccines under the most intense safety monitoring in US history.

If you are fully vaccinated, you can resume many activities that you did prior to the pandemic. Learn more about what you can do when you have been fully vaccinated.

Hundreds of Millions of People Have Safely Received a COVID-19 Vaccine

More than 520 million doses of COVID-19 vaccine were administered in the United States from December 14, 2020, through January 10, 2022. To view the most up to date number of COVID-19 vaccinations that have been given in the United States, please visit the [CDC COVID Data Tracker](#).

COVID-19 vaccines are safe and effective. COVID-19 vaccines were evaluated in tens of thousands of participants in clinical trials. The vaccines met the Food and Drug Administration's (FDA's) rigorous scientific standards for safety, effectiveness, and manufacturing quality needed to support emergency use authorization (EUA). Learn more about EUAs in [this video linked here](#).

Pfizer-BioNTech, Moderna, and Johnson & Johnson/Janssen COVID-19 vaccines will continue to undergo the most intensive safety monitoring in US history. This monitoring includes using both established and new safety monitoring systems to make sure that COVID-19 vaccines are safe.

Serious Safety Problems are Rare

In rare cases, people have experienced serious health events after COVID-19 vaccination. Any health problem that happens after vaccination is considered an adverse event. An adverse event can be caused by the vaccine or can be caused by a coincidental event not related to the vaccine.

To date, the systems in place to monitor the safety of these vaccines have found four serious types of adverse events following COVID-19 vaccination, with evidence that suggests a link to certain types of COVID-19 vaccinations that were administered. They include severe allergic reaction, blood clots, inflammation of the heart muscle, and nerve damage.

Death After Vaccination is Far More Rare Than Death from COVID-19

Reports of death after COVID-19 vaccination are rare. FDA requires healthcare providers to report any death after vaccination to the [Vaccine Adverse Event Reporting System \(VAERS\)](#), even if it's unclear whether the vaccine was the cause. **Reports of adverse events to VAERS following vaccination, including deaths, do not necessarily mean that a vaccine caused a health problem.**

More than 520 million doses of COVID-19 vaccines were administered in the United States from December 14, 2020, through January 10, 2022. During this time, VAERS received 11,225 reports of death (0.0022%) among people who received a COVID-19 vaccine. CDC clinicians review reports of death to VAERS including death certificates, autopsy, and medical records.

A review of reports indicates a causal relationship between Johnson & Johnson's Janssen COVID-19 vaccine and TTS. On December 16, 2021, CDC scientists released a [comprehensive review](#) of reported U.S. cases through December 2, 2021. Continued monitoring has identified additional deaths for a total of nine deaths causally associated with Johnson & Johnson Janssen COVID-19 vaccination. CDC and FDA continue to review reports of death following COVID-19 vaccination and update information as it becomes available.

Figure 12. CDC web page on COVID-19 vaccine safety.

We measured their agreement with statements about research amount (“There is more research on COVID-19 vaccine safety than I thought there was before taking this survey.”), research consensus (“Research on the safety of COVID-19 vaccines is more consistent than I thought before taking this survey.”), and direction of the research (“Research on the safety of COVID-19 vaccines shows a lower rate of adverse reactions than I thought before taking this survey.”) on a 5-point scale.

Procedure. Participants began by reading a brief explanation of the experiment, including details of what they will be asked to do. Participants were first asked for their vaccination status, vaccine intention, and vaccine hesitancy concerns. Next, they were asked to rate the credibility of US-based vaccine research.

Participants were then randomly assigned to one of our three conditions. They were instructed that they will “see a set of information about the safety of COVID-19 vaccines. Please read through the information on the page before moving on with the survey.” After they left the page, they were given an optional text-entry question asking “How (if at all) did the information you just saw affect your opinions about covid vaccine research?”

After interacting with the meta-summary, they were asked about their trust of the information on the page. Next, they were asked the same set of questions about vaccine research credibility, as a pre-post measure. After that, they were asked about the amount, consistency, and direction of vaccine research, before responding to the same questions about vaccine intention and reasons for hesitancy as above, again as a pre-post measure.

Finally, participants were given the short need for cognition (NFC) scale [39], and graph literacy scale [40], before completing a set of demographic questions and ending the survey.

Analysis. For analysis and recruitment, we followed the plan laid out in our pre-registration, with three changes. First, when analyzing intention to get vaccinated, we used a logistic regression instead of an ordinal model due to a failure of the latter to converge as specified. Second, we oversampled to ensure that we had an adequate number of unvaccinated participants, as our

original sampling plan did not take this into account. Finally, we noticed in the qualitative responses that several participants had seemingly copy-pasted sections of Covid-related articles found online. Many of these were identical to each other, and we concluded these were likely either bots, or the same participants using identical responses across IP addresses.

To improve data quality, we decided to remove responses with this type of qualitative answer. First, to ensure we were removing copy-pastes and not just low-effort responses (e.g. “good”, “no”), we first set a minimum character limit of 50 for qualitative responses. Next, we compared each response against all others, until identifying one with a Levenshtein distance of less than 10% the length of the response. This helped identify obvious copy-pastes with minor errors, like the following:

“THE AVAILABLITY OF A SAFE AND EFFECTIVE VACCINE FOR COVID-19”

“THE AAVAILABILITY OF A SAFE AND EFFICTIVE VACCINE FOR COVID-19”

This procedure identified 268 likely bots out of 2393 total unique IDs.

For analysis, although our pre-registration specified we would analyze specific vaccine hesitant sub-groups, we did not observe any differences or interactions between these groups, and chose not to discuss them here due to a lack of theoretical relevance in interpreting our results.

Follow-up Survey. Finally, in order to test longitudinal effects of our meta-summary, we conducted a follow-up survey as well. This survey was not pre-registered, and was developed within the week following our initial survey deployment. It was deployed on MTurk, was made available only to those who had completed our initial experiment, and ran 8-14 days after that experiment. The survey on MTurk was titled “Follow-up survey to "Read about Covid-19 vaccines and answer a survey [March 8-9],” included the description “This is a follow-up to a survey we launched during March 8-9. You will be asked a few questions about what you remember from the vaccine safety research summary you were shown, and how it has affected you.”, and was tagged with the keywords “survey”, “covid”, “vaccine”, “follow-up.”

We first showed them a screenshot of our different conditions to remind them which survey we were referring to. Next, we asked them to indicate which types of activities (“Thought about the research summary from the original survey,” “Mentioned the research summary (or information from it) in a conversation with someone else”, “Searched for research about COVID-19 vaccine safety,” or “Made a decision about whether or not to get vaccinated”) they had engaged in since participating in the original experiment (all on 5-point scales). For each option they indicated, participants were asked to describe in more detail via open text entry. Finally they were asked to rate how much they agreed with the statement “Reading the research summary on COVID-19 vaccine safety helped me feel more confident talking about COVID-19 vaccine safety with others,” whether they had any additional thoughts, and were compensated.

6.5.2 Results

In total, we received 2198 responses after systematically removing responses which did not meet appropriate checks, and analyzed the responses of the 863 of those who were unvaccinated.

Compared to the CDC condition, we found that participants were more likely to agree that there was more research than they thought ($F(2, 871) = 5.15, p = .006, \eta^2 = .012$), more consensus than they thought ($F(2, 871) = 9.65, p < .001, \eta^2 = .022$), and that the research showed they were safer ($F(2, 871) = 15.31, p < .001, \eta^2 = .034$) than they thought before viewing our interventions. Moreover, participants rated our intervention as more trustworthy than the information on the CDC page, $F(2, 871) = 3.36, p = .035, \eta^2 = .008$. See Table 13 for pairwise comparisons.

However, there was no significant effect of our intervention on participants’ concerns about vaccine safety, $F(2, 871) = 0.89, p = .413, \eta^2 = .002$. There was also no effect on their perceived credibility of vaccine science overall, $F(2, 871) = 1.36, p = .256, \eta^2 = .002$. Finally, we ran a logistic regression testing whether participants increased their intention to get vaccinated, but there was again no significant effect (see Table 14).

Comparison	Cohen's d	95% CI	p (Dunnett's test)
Research amount			
Safety only - Base	0.22	[0.07, 0.37]	.004
Full version - Base	0.17	[0.02, 0.32]	.058
Research consensus			
Safety only - Base	0.28	[0.13, 0.43]	.006
Full version - Base	0.21	[0.6, 0.36]	<.001
Research safety estimate			
Safety only - Base	0.36	[0.21, 0.51]	<.001
Full version - Base	0.23	[0.08, 0.38]	<.001
Trust in information			
Safety only - Base	0.19	[0.04, 0.34]	.030
Full version - Base	0.28	[0.13, 0.43]	.087

Table 13. Pairwise comparisons for significant effects.

Variable	β	SE	p	OR
Intercept	-2.55	0.22	<.001	
Safety only	0.20	0.30	.517	1.22
Full version	-0.02	0.32	.945	0.98

Table 14. Logistic regression of intervention condition on increased intention to get vaccinated.

Longitudinal effects. We also found that participants who viewed our intervention were more likely to have discussed it with others than those who viewed the CDC version (see Table 15). There were no significant effects on other longitudinal activities.

Variable	β	SE	p	OR
Intercept	-1.28	0.17	<.001	
Safety only	0.51	0.24	.031	1.67
Full version	0.40	0.24	.098	1.49

Table 15. Logistic regression of intervention condition on whether participants spoke with others about the intervention.

Qualitative results. To help explain our results, we asked participants in both the initial experiment and the follow-up to answer qualitative questions about their initial impressions of the intervention, and the circumstances around any thoughts/discussion/decisions they had in the follow-up.

First, in-line with previous qualitative results, with the amount and consistency of research, and funding sources, were considered useful signals:

First, I didn't realize there had been so many studies on the vaccine, and the correlations of those results were encouraging. I was also encouraged to know that the majority of the research studies were not funded by a government ensuring the science speaks for itself. I would say overall the information slightly improved my feelings towards the safety of the vaccine.

However, there were also a number of reasons the intervention did not work for other participants. First, a number of participants had little trust for science as an institution, believing that researchers may be biased (“I simply don't trust universities either. They are too biased in everything and if anyone even came out with research that shows there's something wrong, they would be canceled and I think that motivates everyone to walk in lockstep with the mainstream narrative.”). This may tie in with the belief that vaccine researchers are financially motivated to publish only positive results (“This information did not change my opinions about vaccine research as I do not believe it is reliable or accurate as researchers are highly motivated to portray the vaccine positively due to enormous financial incentives and funds.”).

Second, there were lingering concerns about potential long-term effects, which participants felt this body of research could not yet address (“It made me feel a bit more confident about it but we still don't know long term effects.”).

Third, as our interventions focused on safety, this was not the main concern for all participants (“I believe that the COVID jabs are "safe", so your research didn't speak to my issue. I haven't

gotten one because they are NOT effective at preventing transmission.”). Even participants in our full version were not convinced of the importance of the vaccines (“I still do not believe it to be safe or effective.”). The above factors, as well as a general lack of trust in pro-vaccine messages (“Y'all are liars and I laugh at your dumb propaganda.”), represent additional obstacles for vaccine safety communication.

For the follow-up survey, in-line with our finding that participants who saw our intervention were more likely to discuss it than the CDC page, we found having clear, transparent numbers may help empower those who have already been vaccinated to have discussions with friends who are still hesitant (“I have a relative who was [...] spouting nonsense. The information I was shown on the survey gave me a few actual facts rather than just calling him an idiot.”).

6.6 Discussion

In this chapter, I showed that meta-summaries of a scientific topic can serve as effective communication tools. Our intervention was successful at informing vaccine-hesitant people about the amount, stability, and valence of COVID-19 vaccine safety research. Importantly, it was considered more trustworthy than information from the CDC website, an important communication platform during the pandemic. I have also shown that an approach using more direct scientific evidence, rather than statements of expert consensus, can be effective at establishing scientific consensus on a controversial topic (Landrum & Slater, 2020).

The question remains, though: How can meta-summaries be most effectively leveraged for science communication on the participatory web? In addition to that: What *specific types* of meta-scientific information are most effective when communicating about controversial scientific topics? And finally: Is this an appropriate approach for topics outside the vaccine space, and if so, what additional considerations might need to be addressed?

In Chapter 7, I will discuss the fifth study in my dissertation, which will address the above questions, digging deeper into the theoretical and practical concerns of the meta-summary approach.

Chapter 7

Study 5: How Meta-Scientific Information Signals Scientific Credibility

7.1 Introduction

In Chapter 6, we developed an approach to vaccine communication leveraging meta-scientific information about COVID-19 vaccine safety research. While this approach had distinct advantages over existing communication (namely, it was considered more trustworthy and raised awareness more effectively than the CDC webpage), there is still much we don't know about how a meta-summary actually works. Specifically, it is unclear what types of meta-scientific information we can use to signal credibility about a scientific domain, what the effects of different types of information might be, and consequently, whether this is a useful strategy for domains outside of vaccine safety.

For example, in the last study, our participants wanted to know how studies were funded (specifically, whether they were funded by corporate entities) in order to establish their credibility. In that case, the vast majority of studies did *not* have industry funding, so the strategy was reasonable. However, what if we tried this for a domain with a much higher proportion of industry funding? What if we summarized other potentially-important indicators of credibility, like open data or materials? Before I can make a blanket recommendation to summarize meta-scientific information, I first need to establish *how* people make sense of that information when thinking about scientific credibility. That is the first goal of this chapter.

The second goal of this chapter is to test this in a participatory web context. To do that, I will introduce a pared-down design of a meta-summary preview suitable for platforms like Facebook or Twitter, conveying key meta-scientific information in a single image. This will thus serve as a preliminary exploration of how we might deploy future meta-summaries on the participatory web.

The third goal is to generalize previous work on credibility judgments of individual scientists (e.g. Song, et al, 2022) onto *summaries* of a larger body of work. Significant past work has examined how people determine whether an individual researcher (or research paper) is credible, but given recent interest in how scientific practices can affect the perception of science as a

whole (Jamieson, et al, 2019), I hope to better understand how people’s perceptions of an entire body of work is susceptible (or not) to information about how that research is funded, conducted, and evaluated.

To do that, in this chapter I introduce Study 5, an experiment testing how different levels of three types of meta-scientific information (peer review status, open data status, and funding source) affect three sub-components of credibility (competence, integrity, and benevolence), among various publics, in the context of a scientific summary. In general, I show that providing these information can significantly affect people’s integrity and benevolence judgments, and that these effects vary significantly across political alignment and propensity for conspiracy thinking.

7.2 Related work

7.2.1 Scientific credibility

In general, there are three things one needs in order to establish credibility: competence, integrity, and benevolence (McCroskey & Teven, 1999; Chen & Dhillon, 2003). Competence is based on their ability and expertise; they need to know what they are talking about in order to be seen as credible. Integrity is based on trustworthiness and reliability; they cannot be a credible actor if they do not reliably provide honest information. Finally, benevolence is based on goodwill; they must act in a person’s best interests, and care about their welfare, if that person is to trust them.

Establishing the credibility of science is important, as it can affect people’s beliefs and behaviors around scientific topics. For example, beliefs about GMO foods are directly affected by the perceived credibility and goodwill of the researchers who develop them (Hunt & Wald, 2020). Unfortunately, at least in the United States context, the perceived credibility of scientists has gone down in recent years (Kennedy, et al, 2022), amidst a landscape of misinformation and conspiracy theories (Wheelock & Ives, 2022). This highlights the need to bolster scientific credibility in the public eye.

Past research has examined scientific credibility from several angles. One important consideration is language use, with scientists being perceived as less credible when they use

enthusiastic (König & Jucks, 2019a), aggressive (König & Jucks, 2019b; Yuan & Lu, 2020), or even polite (Yuan, et al, 2019) language, owing to expectation violations about how scientists are supposed to conduct themselves. Another consideration is how scientific uncertainty is framed. Some studies have found that the use of hedging (i.e. caveats and limitations that highlight scientific uncertainty) can increase (Jensen, 2008; Steijaert, et al, 2020) or decrease (Ratcliff, et al, 2023) the perceived credibility of science communicators, mediated by how it affects their perceived bias. Describing situations where studies disagree can also increase or decrease perceived credibility, depending on the topic (Jensen & Hurley, 2012). In general, these effects appear to be highly context-dependent, and may vary based on both the domain (Jensen & Hurley, 2012) as well as the audience (Ratcliff & Wicke 2022). Given the growing number of studies that show how many factors are at play when evaluating scientific credibility, it is crucial to investigate not only the potential existence of simple main effects, as some have theorized (Jamieson, et al, 2019), but whether and how they are impacted by different contextual factors, such as the audience. In particular, significant prior work (including my own, see the previous chapter) has pointed to conspiracy thinking as an important dimension (Landrum & Olshansky, 2019). Conspiracy thinking can have a significant impact on one's worldview, particularly with regard to one's trust of authority and "official events" (Uscinski, et al, 2020), which can impact the kinds of information one cares about when evaluating information sources.

7.2.2 Meta-scientific information and credibility

Of course, most relevant for this study, some past research has examined the role of meta-scientific information on scientific credibility. For example, knowledge of low replication rates can significantly damage the perceived credibility of researchers in a given domain (for example, psychology; Wingen, et al, 2020). A U.S. national survey found three factors that the majority of the public considered important when evaluating research credibility: funding source disclosure, open data sharing, and peer review status (Jamieson, et al, 2019).

Some links have been made between this meta-scientific information and perceived credibility. For example, past work has found that privately funded research is considered less credible than publicly funded work (Critchley & Nicol, 2011; Rosman, et al, 2022). Additionally, the authors of studies that share open data are considered to be more credible as well, on all three of the

above-mentioned sub-dimensions (Song, et al, 2022). However, this previous work leaves a few questions unanswered, which I seek to answer here:

- Given that it is considered an important factor in scientific credibility (Jamieson, et al, 2019), what role does peer review status have in making these judgements?
- How do these judgements play out in a summary context? While past work has concluded that public funding and open data are generally considered more credible (Song, et al, 2022), how do people make sense of a full body of literature? Does seeing that (e.g.) 50% of studies shared open data improve credible perception? 90%?
- Is there heterogeneity into how these factors affect credibility perception across different people? For example, do people who distrust institutions differentiate between public and private funding? Do they trust peer review to hold researchers to a high standard? It is important to ascertain how different types of meta-summaries can (or cannot) be useful in communicating to this group.

Accordingly, I put forward the following hypotheses. First, there is a strong emphasis on “high-quality work” and “validity” used in common definitions of “peer review” (see below), as well as an positive effects that peer review has on research quality (Goodman, et al, 1994; Garcia-Costa, et al, 2022), implying a more competent research team behind that work. In addition, peer review is meant to uphold standards of scientific integrity (Lüscher, et al, 2020); while certainly imperfect, knowing that a researcher has allowed their paper to pass through the filter of peer review may speak to their integrity compared to one who chose to circumvent (or failed to pass through) this process. Thus,

H7: When the number of **peer reviewed** studies is higher, participants will see the researchers as having higher **competence** and **integrity**.

Additionally, prior work (Song, et al, 2022) found a general increase in the credibility, intelligence, and trustworthy of researchers who shared open data and had public funding. In the case of open data, this information could signal that a researcher is more willing to share information (and thus has less to hide, i.e. more honest), uses sound research practices (i.e. is competent enough to follow existing practices), and is concerned enough about the positive

impact of their work to make the effort to do so. For public funding, these researchers may be seen as free from corporate influences, and therefore less biased in their methods, more honest in their reporting, and conducting research for more altruistic reason. I thus expect that:

H8: When the number of studies with **open data** is higher, participants will see the researchers as having higher credibility on **all three dimensions**.

H9: When the number of studies with **public funding** is higher, participants will see the researchers as having higher credibility on **all three dimensions**.

Next, there are some competing possibilities regarding funding source. Study 4 indicated that people with inclinations toward conspiracy thinking feel funding source is strongly tied to credibility, which may mean they will show a stronger effect of funding source on credibility judgments. There may be some truth to this notion; previous empirical work has shown evidence of a positive bias for studies with private funding (Amiri, et al, 2014; Bhandari, et al, 2004; Bourgeois, et al, 2010; Guillemaud, et al, 2016). There are numerous mechanisms via which bias can be introduced by private funding, such as by prompting researchers to focus on immediate answers to hit deadlines, biasing researchers to pick questions and methods that lead to flattering conclusions for their patrons, or even promote unsound scientific conclusions to be more in-line with a funders agenda (Oreskes, 2021). There is also evidence of an interaction between funding source, credibility, and one's political context, as people in Australia (Critchley, 2008) and Germany (Rosman, et al, 2022) found publicly-funded research more credible, whereas people in Poland (Rowland, et al, 2022) had more faith in privately-funded research. Thus, there is some evidence that funding source may have an impact on the goals and methods of a research team, and that different publics use this knowledge to evaluate research credibility, depending on their own perception of those funders.

However, given that people with less trust of authority/higher conspiracy thinking may regard both public and private entities as untrustworthy (Uscinski, et al, 2020) — and indeed, some qualitative results from Study 4 suggested that many participants did not trust government or

university funding agencies either — it is also possible that they may ultimately be *less* affected by funding source:

SRQ2: Will participants with higher trait-based conspiracy thinking be **more** or **less** affected by funding source when making credibility judgements?

That said, I would generally expect this group to have lower trust of peer review, given a general distrust of science (Kennedy, et al, 2022):

H10: Participants with higher trait-based conspiracy thinking will be **less** affected by peer review status when making credibility judgements

Finally, as an exploratory question:

SRQ3: How do people’s baseline credibility of various scientific domains vary, and does this introduce floor/ceiling effects on how meta-science information affects credibility judgements?

7.3 Methods

7.3.1 Framing

One challenge in determining the link between meta-science information and dimensions of credibility is that the way such information is framed could affect how people make those judgements. By *selecting* and making *salient* certain aspects of a definition, people’s understanding of that issue can be manipulated (Entman, 1993). For example, one could describe peer review as a way to “ensure researchers followed scientific guidelines and met standards of integrity,” or “determine that they conducted high-quality, rigorous work,” or “identified novel effects,” or “did not commit fraud.” So, in order to ensure the meta-scientific information we chose was framed in a way that members of the public were likely to come across, I used existing popular definitions to synthesize a “typical” framing for each.

To do so, I first conducted a set of Google searches to identify articles and other public-facing materials that provided some kind of definition for each. I used the following search terms

(where “X” indicates the name of the information type, e.g. “peer review”): “X,” “X explained”, “X definition”, “X <name of publication> [e.g. “Scientific American,” “New Scientist”].” I collected four publications with explanations or definitions for each type of information (see Appendix G).

For peer review, the sources all made references to experts reviewing a paper prior to publication. They tended to reference its quality as a function of originality/novelty, importance/potential for impact, validity/rigor, and clarity of communication. Synthesizing the above sources, I developed the following definition:

Peer review is when experts in a field review a scientific paper before it is published, in order to ensure only high-quality work is accepted. In general, peer review judges a paper based on its originality, importance, clarity, and validity.

For open data, the focus was often on allowing others to verify or re-do a researchers work, by allowing data to be freely distributed and accessed:

Open data means that the researchers have provided their data to be freely used, re-used and redistributed by anyone. It allows other researchers to reproduce their results independently.

Finally, for funding source, definitions tended to touch on government, industry, and non-profit sources, and emphasized various ways that researchers may use that funding (e.g. equipment, personnel, etc). While one source explicitly mentioned that industry-funded projects may have a slight bias, the others did not, and I chose not to include that statement in order to keep the framing relatively neutral:

Research can require specialized labs, personnel, materials, tools, and money to pay participants. To pay for this, research is usually funded by one of three sources: government, private industry, or non-profit organizations.

7.3.2 *Meta-summary generation*

First, in order to generalize from COVID-19 vaccines as a topic (see Study 4), we picked three topics of relative public importance, with varying levels of controversy associated with them. First, given the low level of public trust around GMO food (Funk, 2018), as well as its relevance to everyday health, we chose it as an example of a “high-controversy” topic. We identified a survey of genetically modified crop safety (Delaney, et al, 2018) to source empirical studies on its health outcomes to summarize.

We also chose multivitamins as another topic of interest. The use of multivitamin supplements has increased dramatically in past decades, although public understanding of its effects (and potential risks) remains low (Sekhri & Kaur, 2014). Despite public-facing advice on their lack of efficacy, multivitamins remain a \$12 billion per year industry (John Hopkins Medicine, 2023). Given its impact, understanding how best to communicate about multivitamin research is an important-but-understudied topic. We identified a meta-analysis of multivitamins on all-cause mortality (Macpherson, et al, 2013) to source empirical studies on the health effects of multivitamins.

Finally, we also wanted to test a field where researchers likely have higher baseline levels of credibility, but whose topic is still relevant to the public. Based on my own past work (see Studies 1 and 3), computing and social science research like that found in HCI was deemed to be a good candidate, with many of our participants reporting high levels of public interest in their domains. We chose to summarize the research on the mental health effects of social media use, as a topic that is directly relevant to millions of people, while to our knowledge not being associated with any major conspiracy theories or distrust. We identified a meta-analysis of social media usage and depressive symptoms (Cunningham, et al, 2021) to source relevant studies.

For each study, I coded them based on their peer review status, open data status, and funding source (see Table 16 for the breakdown of each topic). In general, the number of peer reviewed studies tended to be high, while open data and private funding were fairly low.

Domain	Peer review	Open data	Funding source
Multivitamins	100%	6%	15%

GMO	100%	37%	22%
SM Depression	84%	7%	0%

Table 16. Proportion of various levels of meta-science variables across studies across the three domains in Study 5.

Next, I generated Facebook posts to simulate the scenario of someone coming across a meta-summary shared to social media. These simplified meta-summaries (see Figure 13) included only one visualization (the proportion of a meta-science variable across studies in a given sample) to represent the bare-minimum information we wanted participants to use to make credibility judgements. They also included an explanation of the state of the research, including the number of papers in the summary, the proportion that supported a given claim, the proportion that fell into a specific category (e.g. “90% of the studies were peer-reviewed), and a definition of the meta-science information it visualized.

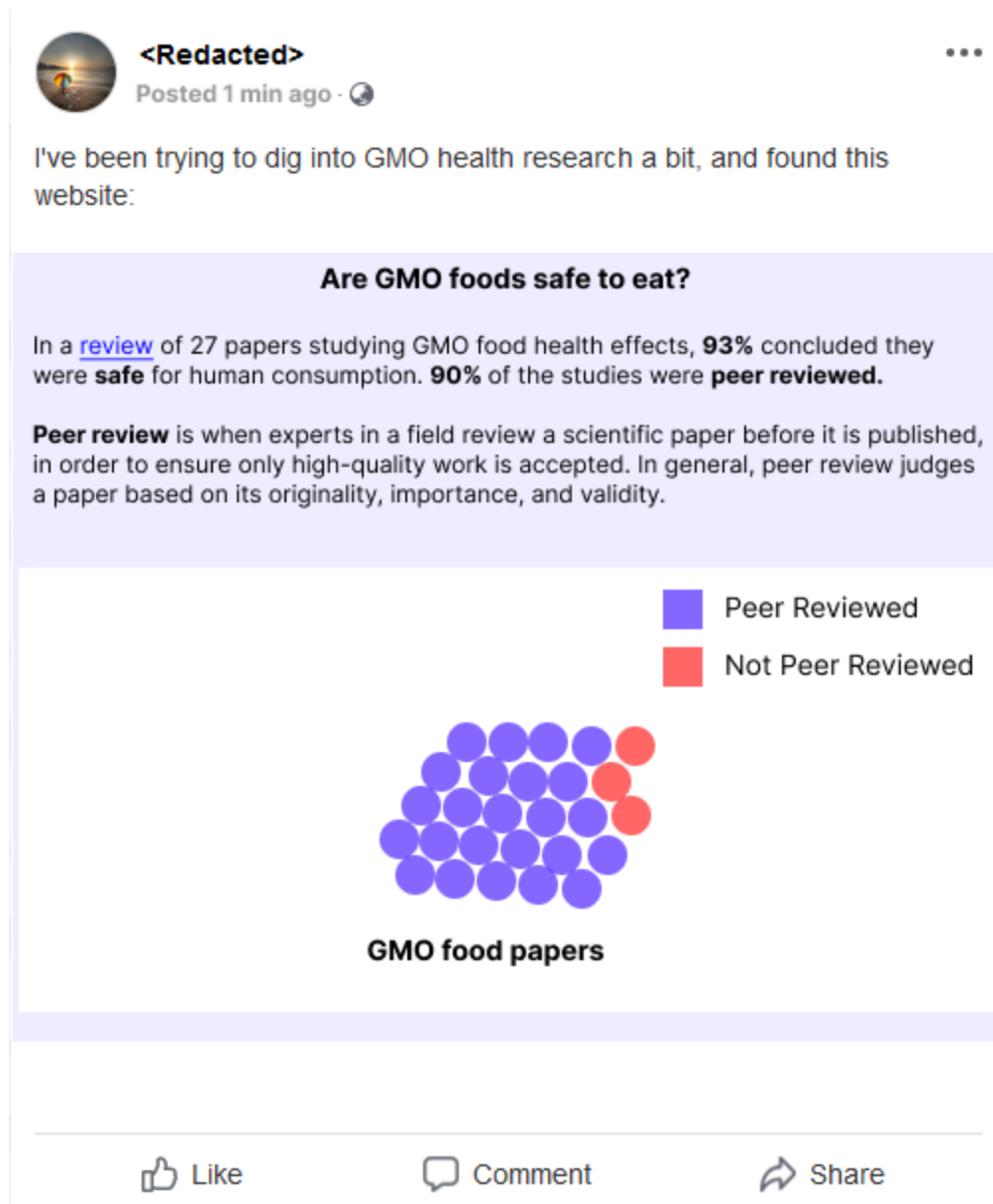


Figure 13. Example of stimulus used for Study 5 (GMO food, peer review, 90% condition). In this post, an anonymous user has posted a link to a meta-summary about GMO food. There are no likes, shares, or comments, and it was posted 1 minute ago to keep participants from inferring anything about the post’s popularity (as in Study 2).

7.3.3 Participants

Participants were recruited via Amazon Mechanical Turk, and were required to have at least a 98% satisfactory task completion rating in order to participate. After removing participants who failed our various checks (see below), as well as those who failed the Levenshtein distance

procedure described in the last chapter, there were a total of 469 respondents (down from a total of 808). The mean age was 36.82 (sd = 10.75). By race, there were 377 (80.0%) White, 63 (13.4%) Asian, 18 (3.8%) Black, 5 (1.4%) American Indian or Alaska Native, and 1 (0.2%) Native Hawaiian or Pacific Islander. The majority (318) had a Bachelor's education (67.8%), 84 (17.9%) had a Masters degree, 35 (7.5%) had a high school education or GED, 27 (5.8%) had an Associate's degree, and 4 (0.8%) had doctorates. Politically, 106 (22.6%) described themselves as very conservative, 89 (19.0%) were somewhat conservative, 41 (8.7%) were neither conservative nor liberal, 143 (30.5%) were somewhat liberal, and 90 (19.2%) were very liberal.

7.3.4 *Measures*

Credibility was measured with a modified version of McCroskey and Teven's (1999) questionnaire, as per Ratcliff, et al (2023), with participants rating how certain adjectives described researchers' on a 1-5 scale for competence (intelligent, expert, incompetent), integrity (trustworthy, ethical, dishonest), and benevolence (care about other people, have other people's best interests at heart, self-centered). We measured conspiracy thinking with a one-item questionnaire: "I think that the official version of events given by authorities very often hides the truth." (Lantian, et al, 2016) on a 5-point scale. We also measured self-reported scientific expertise: "I consider myself an expert in scientific topics" on a 5-point scale.

7.3.5 *Procedure*

First, participants were introduced to the study and asked about their conspiracy thinking and scientific expertise. They were then asked to rate their baseline perceived credibility of researchers who study "GMO food safety," "the health effects of multivitamins," and "the health effects of social media." After that, they were given a captcha test to help determine which participants were bots (as per Aguinis, et al, 2021), then randomly assigned to three scenarios, which were described as follows:

Imagine you're scrolling through Facebook, and you see that someone has shared a social media post about [GMO food/multivitamins/the mental health effects of social media]. Read through the post below before continuing with the study.

Keep in mind, this is a **hypothetical scenario**.

For each scenario, participants were randomly assigned to one level of topic (GMO food, multivitamins, social media), meta-science information (peer review, open data, funding source), and proportion (10%, 50%, 90%), reflected in the screenshot they saw. This way, each participant was exposed to one level of each variable. Following each scenario, they were asked to rate the credibility of the researchers who conducted the studies in the scenarios, and asked “How did the information on the last page affect your overall impression of the researchers?” as an open-ended text-entry question.

After reading each of the three scenarios, participants were asked a set of demographic questions (age, gender, race, ethnicity, education, and political leaning), as well as a multiple-choice attention check question (Which scientific topic did **NOT** appear in any of the scenarios you just read? [GMO food/multivitamin health effects/social media and depression/climate change]), as per Aguinis, et al, (2021).

7.4 Results

Analyses and procedures were pre-registered here: https://aspredicted.org/Y3V_LF5

7.4.1 Differences across domains

Before moving to the main effects of meta-science information, SRQ3 asked how people’s baseline credibility of various scientific domains vary, and whether this might introduce floor/ceiling effects on how meta-science information affects credibility judgements. However, participants' initial impressions of each research field were highly similar, and generally softly positive (see Table 17). With respect to potential ceiling effects, however, it is notable that credibility judgements tended to decrease in most cases rather than increase after seeing meta-science info (see Figure 15 below).

Dimension	Topic	Mean (SD)
Competence	GMO	3.88 (0.69)
	Multivitamins	3.89 (0.70)

	Social Media	3.79 (0.63)
Integrity	GMO	3.77 (0.73)
	Multivitamins	3.86 (0.67)
	Social Media	3.74 (0.68)
Benevolence	GMO	3.35 (0.65)
	Multivitamins	3.47 (0.63)
	Social Media	3.40 (0.63)

Table 17. Means and standard deviations of credibility perception, across topics (scale ranged from 1-5).

7.4.2 Main effects

For a visualization of the main effects across information type, ratio, and sub-dimensions of credibility, see Figure 14. Notably, the only significant *increase* in credibility relative to baseline was participants rating researchers in the 90% open data conditions as more benevolent (and a marginal increase in benevolence in the corporate funding 10% condition, and a marginal increase in integrity for the peer review 90% condition). Other conditions seemed to be similar, or decrease relative to baseline (perhaps owing to high baseline levels of credibility across conditions; see discussion).

Peer review. Looking first at the effects of peer review, we can see that H7 is partially supported (see Table 18). Higher levels of peer review was associated with higher judgments of integrity, but not competence. It was also not associated with any difference in benevolence estimates.



Figure 14. Effects of different ratios of metascientific information on sub-dimensions of credibility. Y axis indicates the difference between pre- and post-intervention credibility scores. Error bars shown are 95% CIs. Plots with a * are statistically significant.

Model 1: Competence			
Variable	β	SE	p
Intercept	-0.1943	0.0533	<.001
Peer review ratio	0.0012	0.0008	=.162
Model 2: Integrity			
Variable	β	SE	p
Intercept	-0.2550	0.0548	<.001
Peer review ratio	0.0031	0.0009	<.001
Model 3: Benevolence			
Variable	β	SE	p
Intercept	-0.1114	0.0544	<.001
Peer review ratio	-0.0002	0.0009	<.849

Table 18. Linear models estimating sub-dimensions of credibility, based on the ratio of peer reviewed articles in a summary.

Open data. H8 was also partially supported (see Table 19); participants who saw a higher ratio of articles with open data judged those research fields as having more integrity and benevolence, but not competence.

Model 1: Competence			
Variable	β	SE	p
Intercept	-0.1366	0.0535	<.001
Open data ratio	0.0005	0.0009	=.601
Model 2: Integrity			
Variable	β	SE	p
Intercept	-0.2567	0.0560	<.001
Open data ratio	0.0031	0.0010	=.002
Model 3: Benevolence			
Variable	β	SE	p
Intercept	-0.2423	0.0590	<.001
Open data ratio	0.0039	0.0010	<.001

Table 19. Linear models estimating sub-dimensions of credibility, based on the ratio of articles with open data in a summary.

Funding source. Finally, once again, H9 was only partially supported (see Table 20); participants who saw a higher ratio of articles with private funding judged those research fields as having less integrity and benevolence, but not competence.

Model 1: Competence			
Variable	β	SE	p
Intercept	-0.1249	0.0512	=.015
Open data ratio	0.0007	0.0008	=.418
Model 2: Integrity			
Variable	β	SE	p
Intercept	-0.0432	0.0614	=.482
Open data ratio	-0.0021	0.0010	=.038
Model 3: Benevolence			
Variable	β	SE	p
Intercept	0.0334	0.0594	=.573
Open data ratio	-0.0023	0.0010	<.018

Table 20. Linear models estimating sub-dimensions of credibility, based on the ratio of articles with private funding in a summary.

7.4.3 *Heterogeneous effects*

For the distribution of how participants self-described their conspiracy thinking and politics, see Table 21.

Conspiracy thinking (1 = lowest, 5 = highest)				
1	2	3	4	5
60	171	237	696	243
Politics (1 = most conservative, 5 = most liberal)				
1	2	3	4	5
318	267	123	429	270

Table 21. Distribution of conspiracy thinking and politics in our sample.

Conspiracy. SRQ2 asked whether participants with higher trait-based conspiracy thinking will be more or less affected by the funding source when making credibility judgements. Given the significant effects of funding source on integrity and benevolent judgments (see above), I tested models using conspiracy thinking as an interaction (see Table 22), and found a marginal interaction whereby people with higher conspiracy thinking showed a stronger effect of funding source on their judgements of benevolence (other interactions had $p \geq .1$). This can also be illustrated by segmenting participants who had lower conspiracy thinking (answered “1” or “2”) and those with high conspiracy thinking (answered “4” or “5”). Those with high conspiracy thinking showed significantly higher benevolence estimates when industry funding was low ($p = .005$), but those with low conspiracy thinking did not ($p = .878$).

Conspiracy thinking x Funding Source -> Benevolence			
Variable	β	SE	p
Intercept	-0.5901	0.2321	=.011
Funding source ratio	0.0049	0.0038	=.195
Conspiracy thinking	0.1684	0.0605	=.006
Conspiracy x ratio	-0.0019	0.0010	=.051

Table 22. Linear model estimating the interaction effect of conspiracy thinking on the effects of funding source on benevolence perception.

H10 predicted that participants with higher trait-based conspiracy thinking will be less affected by peer review status when making credibility judgements. However, there were no significant interactions when testing against previously significant models.

Politics. Although I did not have any specific predictions about how political affiliation would interact with metascience information effects, I ran exploratory interaction models given its importance in science communication (e.g. Funk, 2020). Overall, there were two significant interactions, with liberals showing a stronger effect of open data status on integrity and benevolence judgements than conservatives (see Table 23). Again, this is borne out with participants describing themselves as “somewhat liberal” or “very liberal” showing highly

significant effects of open data on integrity ($p < .001$) and benevolence ($p < .001$) perception, but those describing themselves as “somewhat conservative” or “very conservative” did not ($p = .203$ and $p = .256$, respectively).

Politics x Open data -> Integrity			
Variable	β	SE	p
Intercept	0.0363	0.1230	=.780
Open data ratio	-0.0012	0.0023	=.604
Politics	-0.0956	0.0382	=.013
Politics x ratio	0.0014	0.0007	=.037
Politics x Open data -> Benevolence			
Variable	β	SE	p
Intercept	0.0791	0.1270	=.540
Open data ratio	-0.0008	0.0022	=.715
Politics	-0.1051	0.0374	=.005
Politics x ratio	0.0015	0.0007	=.019

Table 23. Linear models estimating the interaction effects of politics on the effects of open data on integrity and benevolence perception.

7.5 Discussion

Study 5 was designed to dig deeper into the effects of meta-summaries, by isolating different types of meta-science information and different types of participants. Overall, the results indicate that a) meta-science information, as typically described in the media, is connected with the public’s judgements of scientific credibility, b) these effects vary by information type, and c) these effects may also vary by various participant characteristics, such as conspiracy thinking and political alignment.

There are a few important things to note here. First, across information types, there were no significant effects on competence estimates; initial estimates of researchers’ competence were

high, and there were no significant differences across peer review status, open data status, or funding sources. This is in contrast with past work (Song, et al, 2022), perhaps indicating a difference between estimating a specific researcher's competence compared to the competence of an entire field. That is, this may be an example of the "soft positive" (Funk, 2017) perception of scientists, where they are generally considered capable. While an individual researcher may be poor at their job (Song, et al, 2022), perhaps it takes more to disabuse people of their notion of researchers as experts in their field.

This may also be in-line with the fact that scientific conspiracy theories are more often based around cover-ups, fraud, and negative intentions, rather than incompetence (e.g. Natoli and Marques, 2021). They generally presuppose a group of people hatching plots, hiding information, and working against the public good (Enders & Smallpage, 2019), concerns more closely related to integrity and benevolence than competence.

Second, perhaps because of the high average credibility judgments already, most meta-summaries seemed to decrease perceived credibility (only seeing a 90% open data ratio significantly improved benevolence judgments relative to baseline). There are a few possible implications here. First, if people generally have high opinions of researchers' credibility, any increase relative to that baseline may tend to be marginal. Alternatively, it may be that even a 90% ratio may be too low, and displaying a higher ratio (e.g. 100%) could increase credibility compared to baseline. In either case, showing high numbers of credibility indicators in the literature had neutral-to-positive effects overall, suggesting a meta-summary approach may only increase trust for fields who have substantially adopted these practices. Given the descriptive findings on what these ratios look like in practice (refer back to Table 16), showing peer review and funding source may have a positive impact across these fields, while showing open data (whose ratio ranged from 7%-37% in practice) may not.

Third, when combining the above insight with the interaction effects identified, this study shows that providing meta-science information can have different effects depending on the domain, the audience, and the type of information. While past work has shown strong average effects for open data and funding source (Song, et al, 2022; Critchley & Nicol, 2011; Rosman, et al, 2022),

these effects appear to vary among those with different politics and propensities for conspiracy thinking. So, while showing (e.g.) funding source information appeared to be an effective approach for vaccine communication (see Chapter 6), the usefulness of a meta-summary may depend on different publics' preconceptions of various scientific fields. Based on the present findings (corroborating those from Study 4), it appears funding source plays a larger role for those with high conspiracy thinking, whereas open data is not as convincing to conservatives.

These findings highlight the potential for tailoring meta-summaries to different audiences. Ideological tailoring by framing messages according to one's values is a powerful approach in science communication (Luong, et al, 2019), but the findings from Study 5 show that the underlying meta-scientific evidence within a message can have different effects for different audiences. For example, given the relationship between political extremism and conspiracy thinking (Van Prooijen, et al, 2015), far-right conspiracy theories may be convinced by funding source information, whereas far-left conspiracy theories may see open data as a strong signal of credibility.

Overall, Study 5 has helped develop our understanding of meta-science information as a science communication tool, showing that providing such information in a participatory web context can significantly affect people's judgments of researchers' credibility. In particular, it has highlighted the importance of adapting communication strategies for different audiences, given people's different baseline levels of credibility perception, and the difference in how specific types of information affect different audiences. Finally, in the next chapter, I will bring together the main findings from my dissertation work as a whole, show how it supports my overall thesis statement, and discuss overarching implications for research, design, and policy.

Chapter 8

Discussion

8.1 Circling Back

Throughout this dissertation, I have discussed several studies (1, 2a, 2b, 3a, 3b, 4a, 4b, 5) examining science communication on the participatory web. Here, I will more fully describe how they come together to answer the research questions I laid out in Chapter 2, and how they support my thesis statement.

8.1.1 RQ1: How do the affordances of participatory web technologies affect the way science information is conducted, perceived, and engaged with?

Studies 1 and 2 showed how the design of participatory web platforms plays a major role in the flow of science communication online. On the researchers'/communicators' side, the potential to reach a vast network of diverse publics is undercut by a lack of targeting mechanisms, low information about one's audience, and inadequate space to properly contextualize one's work. On the readers'/audiences' side, the discussions that surround scientific content can serve as noisy heuristics of their quality, disincentivizing them from reading a given paper, article, or post. In both cases, these features of participatory web platforms end up blocking the flow of useful scientific information. By identifying these barriers and putting forward related research and design implications, I hope to continue and inspire future work to improve the utility of these platforms for science communication.

8.1.2 RQ2: How can we design tools to support science communication and public scholarship by researchers on the participatory web?

Study 3 served as a case study for how we can build tools to address some of the barriers identified via RQ1. Namely, we examined how audience analytics can help researchers improve their science communication endeavors on sites like Twitter. Ultimately, we found that by providing quantitative and qualitative insights about one's typical audience, researchers can better gauge their success, frame their work more thoughtfully, and conduct science communication and public scholarship in a more informed way. Study 3 is an encouraging example of the potential for new tools to improve the flow of science communication on the participatory web.

8.1.3 RQ3: How can providing meta-scientific summaries of research questions help improve people's awareness of, opinions on, and understanding research on the participatory web?

Studies 4 and 5 consisted of the background research, design, and evaluation of meta-summaries. In Study 4, we showed how summarizing relevant meta-scientific information about the safety of COVID-19 vaccines improved people's awareness and understanding of that research, in a way that was considered relatively trustworthy. In Study 5, we showed how different types of meta-scientific information affected people's opinions of various types of researchers, particularly their integrity and benevolence, in a participatory web context. While there is much more work to be done evaluating and expanding on this approach, Studies 4 and 5 highlight the usefulness of meta-scientific information in communicating about controversial scientific topics.

8.1.4 Thesis statement

As a reminder, my thesis statement for this dissertation claimed:

By better understanding the flow of scientific information online (RQ1), designing technology to connect researchers with relevant stakeholders (RQ2) and communicating meta-scientific knowledge to the public (RQ3), we can support online science communication and increase their awareness, engagement, understanding, and trust of science.

Breaking down the claims, each one describes how better science communication can be achieved, in this case referring to awareness, engagement, understanding, and trust. The first claim ("understanding the flow of scientific information online") can help achieve these outcomes by identifying where the science communication flow breaks down, what platform affordances lead to those breakdowns, and what future work is required to deal with those breakdowns. Understanding a problem is the first step toward solving it, and through Study 1 and Study 2, I have enumerated how the barriers of participatory web platforms can reduce, block, or distort the "supply" of scientific knowledge online, lead to misinformation or misunderstandings, and reduce engagement between researchers and the public.

The second claim (“designing technology to better connect researchers with relevant stakeholders”) is addressed by Study 3. There, I described how audience analytics can inspire researchers to target non-researchers (to increase awareness and engagement) and frame their work to better suit their audience’s needs (to increase understanding and engagement). While Study 3 was just one example, it shows the potential for technology support to improve researchers’ science communication online, with the ultimate goal of improving the AEIOU outcomes of science communication (Burns, et al, 2003).

Finally, the third claim (“communicating meta-scientific knowledge to the public”) was supported by Studies 4 and 5. First, I found the meta-summary on vaccines was considered a more trustworthy alternative to the CDC webpage, while significantly increasing awareness and understanding of the relevant research. Moreover, it was more engaging as well, with those who saw it being more likely to discuss the meta-summary with others in conversations about the vaccine. Study 5 showed that there is a strong connection between various types of metascientific information and credibility perception. Notably, I found that it could *decrease* as well as increase trust, depending on the state of the literature in question, so some care is required in determining in what cases this is a useful approach in establishing credibility. Nevertheless, it is clear that providing metascientific information can significantly shape the public’s trust of science.

Overall, by supporting researchers (Studies 1 and 3), understanding the needs of different publics (Studies 2 and 4a), and designing more effective and trustworthy messaging (Studies 4b and 5), this work represents a holistic approach to the study of science communication on the participatory web. For the remainder of this chapter, I will describe what I consider to be the most important next steps for this line of work, laying out an agenda for researchers, designers, and policymakers to consider. I will start with a few high-level takeaways for people who want to do science communication, before diving deeper into the specific implications for research, design, and policy.

8.2 Implications for Researchers who want to Reach Out

Science communication is important. I more or less covered this in Chapter 2, but beyond the reasons explained there, the work in this dissertation should be encouraging. In Study 1, we saw how researchers could get their work in front of people who could use it, spark conversations about scientific issues, and use their publicity as evidence of impact for funding bodies. You (as a researcher) may have a larger potential audience than you think (according to Study 3), and you may be in a position to share research that people use to make important decisions in a way that is more accessible, useful, and easier to understand (according to Study 4).

Consider your goals. There are numerous reasons to do science communication, so consider, what are yours? Imagine you published a paper on the effects of screen time on childrens' sleep habits. Who should know about this? Researchers in your field, yes, but perhaps also new parents. Where can you find that audience? Maybe friends on Facebook, maybe circles on Twitter, maybe parenting subreddits or other specialized forums. How do you frame your work? Consider the stakes involved, start with a question, and highlight why this is an important topic. What you probably don't want to do is tweet a link to your paper into the void. Science communication is difficult, but as was apparent in Study 3, just considering one's audience is an important first step.

Consider the danger. Our participants in Study 1 reported harassment and backlash, based on their own identities, the topic of their research, and the political climate. Negative discussions can arise when your research breaks into publics you may rather avoid (Study 3), and these discussions can affect how other people engage with your work (Study 2). Given changes to Twitter in the past year, especially with regard to its moderation practices and propagation of certain accounts' comments, the risks of harassment may be amplified. It may be worth considering the tradeoffs of different platforms, based on their network effects, dominant cultures, and capacity for interaction, when thinking about whether to do this work at all.

Signal credibility, and describe the process. In Study 5, we saw how certain meta-scientific information (funding source, peer review, and open data) can affect people's perception of scientific credibility. This illustrates that people care *where scientific knowledge comes from*, and *how it is produced*. When discussing your own work, it may be worth describing these details if

working in a space where credibility is a concern. However, even if you are not, there is value in understanding the process by which scientific knowledge is generated (see e.g. Oreskes, 2019, Oreskes 2021, Osborne, et al, 2022). As illustrated in Studies 4 and 5, how people (mis)understand the process of research can color how they appraise it, so by providing insight into “how the sausage is made,” so to speak, we can give non-experts clearer perspective on how to engage with scientific knowledge.

8.3 Implications for research

8.3.1 Cross-disciplinary models for science communication

As outlined by a recent summary of the research on science communication, there has historically been insufficient attention to disciplines outside of medicine and ecology (Gerber, et al, 2020). In this dissertation I focused on several different fields, and although I did not initially set out to draw comparisons between them, there are a few lessons to consider when thinking across disciplinary lines. Namely, supporting the science communication of a specific discipline requires understanding its particular audiences, researchers, and scholarly outputs.

First, consider how audiences might vary across disciplines. In Study 3, we identified numerous practitioner groups who regularly followed HCI researchers; designers and software engineers were most prominent, but we also saw lawyers, physicians, teachers, business administrators, artists, and policymakers. For these audiences, their primary concern may be translating research findings into their professional practice (Colusso, et al, 2019), or professional networking (Forte, et al, 2012), both scenarios our participants in Studies 1 and 3 were aware of. Contrast this with vaccine safety research, where audiences were often highly skeptical domain non-experts, sometimes motivated to do significant secondary research on the topic, sometimes outright deniers or conspiracy theorists. Some followed researchers on Twitter, others followed alternative sources on less mainstream platforms, while others still were completely disengaged from the topic. Contrast again with the health research used in Study 2, a topic of interest to many participants, but with lower stakes and fewer widely-believed conspiracies. Already, we can see audiences vary by *expertise in the material, professional relationship, goals, trust of research, presence on participatory platforms, and motivation*. Each of these factors played an important role across the studies in my dissertation.

Next, consider the researchers themselves. In the post-normal age, researchers play an active role in public dissemination of scientific information (Brüggemann, et al, 2020), but their behavior varies widely from discipline-to-discipline (Holmberg & Thelwall, 2014), and individual-to-individual (see Studies 1 and 3). We found that motivations can include self-promotion, funding, providing knowledge, and improving public trust and understanding of science; however, some researchers have no interest in doing this work at all. Researchers need to contend with the dangers of backlash and harassment, which vary across topics and personal identities. Researchers need to consider the skill involved in disseminating their work, and some have cultivated much larger platforms than others, allowing them to reach publics others may not (or only sporadically) have access to. Thus, the *expertise, motivation, culture, reach, and risks* of science communication are an important source of variance when considering the researchers' perspective.

Finally, the scholarly output of a given field is another important consideration. We have discussed relevance to certain groups, which may lead to some topics being more *emotionally charged* than others. Some topics may also be more technically complex (e.g. the ingredients in mRNA vaccines), presenting a more significant communication challenge (Ecklund, et al, 2012). Some lines of research may generate completely different types of knowledge (e.g. experiments, interviews, simulations, ethnographies, built artifacts), which cannot be effectively communicated the same way or even via the same channels. Thus, we must consider the *applicability, emotional stakes, complexity, appropriate channels, and specific communication skills* according to each given discipline.

Overall, this paints a complex picture of science communication. In order to generalize across disciplines, generate insights for science communication researchers and practitioners, and facilitate discovery of new effects and strategies, it is important to understand how these various factors interact by rigorously modeling them (Devezer, et al, 2019). While it is beyond the scope of this dissertation to introduce a formal model of cross-disciplinary factors in science communication, Table 24 explores how some of these factors vary across two of the topics I touched on here.

Audience Factors					
Discipline	Expertise	Professions	Goals	Trust	Platforms
HCI	Variable	Designers, engineers, educators, etc.	Improve professional practice, technology habits...	Mid-high	Twitter (high), Facebook, Reddit
Vaccine safety	Low	NA	Decision to vaccinate themselves, family	Variable (extremely low to high)	Twitter, Facebook, alt sources

Researcher factors				
Discipline	Expertise	Motivations	Reach	Risk
HCI	Low-high	Self-promotion, funding, impart knowledge, build public understanding	Low-high	Low-mid
Vaccine safety	Low-high	Impart knowledge, build public trust	Low-very high	High

Scholarly factors				
Discipline	Applicable	Complexity	Stakes	Channels
HCI	Mid-high	Low-mid	Low-high	Social media, demos...
Vaccine safety	High	Mid-high	High	Social media, physicians...

Table 24. Example of disciplinary differences for science communication.

As is apparent, the complexity of interactions between these factors is vast, and leads to numerous potential challenges. For example, what should be done if the platforms that audiences exist on (e.g. Twitter) do not support the type of communication ideal for a specific research product (e.g. a live demo)? How can we reach stakeholders in alternative media ecosystems, particularly when the risks of backlash and harassment are already high? How do we deal with low-trust disciplines when certain communication strategies are not appropriate (see Study 5)? Formalizing these variables and interactions could help align disparate strands of research

(Gerber, et al, 2020), and build best practices for science communication across disciplines and contexts.

8.3.2 Modeling platform features as they relate to science communication

Studies 1 and 2 provided useful insights into the effects of various platform features and affordances for how both researchers and various publics interact with scientific information on the participatory web. This work highlights the importance (and potential consequences) of those features, but more work can be done to map out how each feature relates to science communication issues. This is important for two reasons.

First, platforms come and go. For example, changes to Twitter's ownership and subsequent issues (deprecation of its free API tier, migrations to other platforms) made its future as a hub for science communication uncertain (Stokel-Walker, 2022). In order to ensure that our scholarship remains relevant after these platforms disappear, we need to understand the relationship between specific features and their downstream consequences for science communication. If we know that the character limit on tweets is a challenge for researchers trying to contextualize their work, it stands to reason it could also lead to misunderstandings or misinformation on Mastodon, Threads, or future microblogging platforms. The lack of clear operationalization of media affordances is a known issue (Rice, et al, 2017), so building clearer models of how participatory platforms relate to science communication issues and outcomes is critical.

Second, theory-building in this space could inform the design of more effective plug-ins, features, or platforms for science communication. For example, given the potentially misleading use of user comments as a heuristic for article quality (see Study 2), we could design plug-ins to highlight article qualities following uses and gratification theory, an approach that could apply to (e.g.) Twitter or Facebook just as easily as it could to Reddit. By understanding science communication on the participatory web more deeply, we can anticipate how new developments in the landscape of participatory platforms might impact the ecosystem of science communication and public scholarship, and develop solutions with those predictions in mind.

8.4 Implications for design

Current platforms could be vastly improved, in terms of their usefulness for science communication. See Table 25 for a brief description of each.

Problem	Study
Not enough space to provide context for research	Study 1
Difficult to target specific audiences	Study 1
Lack of success metrics and feedback	Study 1
User comments are noisy heuristics of quality	Study 2
Research can be seen by hostile publics	Study 3
Papers are often shared with paywalls, un-summarized	Study 4
Isolated papers and headlines can be confusing, contradictory	Study 4

Table 25. List of challenges with current participatory web platforms, by study.

While the individual chapters explored these issues and opportunities in isolation, I want to discuss some cross-cutting implications here, as a larger agenda for the design of participatory web platforms for science communication.

8.4.1 Provide support for non-expert publics to engage with science. My work has uncovered a number of challenges that people face when engaging with scientific information online, including a lack of context (Study 1), potentially misleading heuristics about article qualities (Study 2), and difficulties accessing, parsing, and using scientific papers (Study 4). This dovetails with previous work uncovering similar challenges, such as misleading or sensationalized scientific headlines (Dempster, et al, 2022) being taken out of context on social media (West & Bergstrom, 2021). Thus, one overarching class of potential design implications is to better support non-experts in seeking out, assessing, and using scientific information on participatory web platforms.

Such designs could take a number of forms. For example, Study 4 showed the potential for additional context around a scientific topic (e.g. quantity and consistency of results) in informing people about that topic, and determining what to trust. Given the potential for real-time

corrections of scientific misinformation on social media (Vraga & Bode, 2020), one possibility would be to implement a similar intervention by placing scientific headlines in a broader context. For example, by using open data platforms to identify related papers (Kinney, et al, 2023), it would be possible to summarize the broader research context and weight of evidence behind scientific headlines, highlighting their nuance (Study 1), utility (Study 2), and credibility (Studies 4 and 5).

8.4.2 Provide more control over researchers' audiences. The capacity to target messages to specific groups already exists on social media platforms in some capacity. For example, on Facebook, one can broadcast messages to customized groups of friends, to varying effect (Oeldorf-Hirsch & Gergle, 2020). However, this approach is hardly scalable; it is impossible to manually select every person in a given platform one does or does not wish to see a science communication message. Instead, perhaps an approach similar to what we used with Ripple (see Study 3) could be used to categorize users according to their own self-descriptions. Those users could opt-in to being pushed posts, videos, or papers intended for people like them.

On the other hand, perhaps researchers could choose to hide certain posts from specific publics, in order to avoid any risk of harassment or backlash for topics they know to be sensitive. This would be in-line with calls for more consensual systems, whereby users can more effectively anticipate and control the consequences of their actions on participatory platforms (Im, et al, 2020).

Of course, such a categorization scheme should also contend with privacy concerns. Information privacy concerns can vary widely across contexts (Wu, et al, 2020), with different types of users reacting to social media privacy issues with fear, acceptance, or indifference (Marreiros, et al, 2015). One important consideration is expectation violations (Fiesler, et al, 2018), where users do not anticipate shared information on social media being used in a certain way. With Ripple, we categorized users via their bios, generally understood as a means of public self-presentation (Pathak, et al, 2021). However, what about approaches that use things like posting behavior or content? Connections to other users? Groups/list membership? Understanding where to draw the boundaries when summarizing audience insights is an important consideration for future work in

this space, given differing expectations with how different types of data are used across different platforms (Fiesler, et al, 2018).

8.5 Implications for policy

8.5.1 Incentivizing science communication, in many forms

From a policy perspective, recent calls have been made for academic departments to consider science communication as an integral part of academics' responsibilities and consider them for tenure promotion (McCall, et al, 2016), citing that engaging in public discourse around one's work is one of the reasons tenure exists in the first place (Sugimoto, 2016). Although organizations like the NSF formally value "broader impact" (of which dissemination is a component) (March, 2007), findings from Study 1 suggest that the culture of (at least) HCI still does not adequately signal to all researchers that communicating about one's own work is a valued activity. Thus, perhaps providing clear career incentives for science communication could help signal the value of this work for those who feel uncomfortable with it.

Of course, such incentives would need to take into account the potential exclusion of women and minorities in mainstream news reporting or discrimination on social media (McCall, et al, 2016), and should be crafted so as not to unfairly discriminate against those who may have difficulty gaining broad public exposure. It would also need to consider the high level of harassment and abuse faced by researchers in certain medical fields (Grimes, et al, 2020), or who work on topics that may be emotionally charged (see Study 1). There is also a balance between topics that are highly controversial, but are of high public interest; while participants in Study 4 often distrusted the vaccine literature (and some were even distrustful of our research team), they were also highly motivated to seek out information in this space. How might a department calibrate expectations for a vaccine researcher compared to (e.g.) a nephrologist? Such a policy would likely require fine-tuning to incentive science communication while remaining broadly equitable, but given both the significant effort required to do this work well, as well as the potential benefits, I maintain that it is a worthwhile goal. One possibility may be to encourage more synthesis work; given the utility of a meta-summary approach (Studies 4-5), encouraging researchers to discuss broader scientific topics with an eye toward consensus communication and

credibility signals could be a useful way to participate in science communication while allowing flexible outlets for those whose own research may be difficult or dangerous to discuss.

While previous proposals have laid the groundwork for what formal recognition of science communication might look like (McCall, et al, 2016), I want to briefly build on them here. First, evaluating the impact of science communication is hard (Jensen, 2016). However, based on my work and others', there are a number of ways to determine how successful a given attempt was. These could range between audience analytics for social media impact (which, beyond raw readership/impressions, could determine whether important stakeholders are being reached on social media; Study 3), discussions around articles and blog posts (Jones, et al, 2019; Study 2) with an emphasis on key outcomes identified in Study 1 (information utility, engagement, broader understanding of science), or even Google trends and other large datasets to measure interest in a given topic at a longer timescale (Nghiem, et al, 2016). For some examples of how different sources of data might speak to Burns, et al's (2003) science communication outcomes, see Table 26.

Outcome	Measures
Awareness	Audience impressions (e.g. via tools like Ripple), site traffic
Enjoyment	Likes, shares, comment content, comment sentiment
Interest	Search data (e.g. via google trends), number of posts/discussions on a topic
Opinion	Comments (content analysis, sentiment analysis), surveys
Understanding	Comments (qualitative analysis), surveys

Table 26. Indicators of science communication outcomes on the participatory web, based on the AEIOU outcomes from Burns, et al (2003).

Moreover, by conducting further research into impact measures for science communication, we can better establish the success of individual efforts, making it easier to incentivize as a normal part of scholarly work (as I argue in Chapter 3).

8.5.2 *Syncing scientific practice and the public's understanding of credibility*

Finally, the results of Study 5 showed that the meta-scientific status of a body of research (e.g. peer review, open data, funding) had a significant effect on people's judgments of those researchers' credibility. When more studies were peer reviewed, publicly shared their data and materials, and were funded by non-corporate entities, the researchers responsible were seen as having greater integrity and benevolence. I think there are two important implications here.

First, echoing Jamieson, et al (2019), research should be conducted in such a way that the public at-large can be confident in its credibility. While adopting practices like open data can improve the accessibility, quality, and reproducibility of research (Hardwicke, et al, 2018), my work also affirms that when a research field signals that they employ these practices, it improves the public's trust in that field. In a time of declining trust in science (Kennedy, et al, 2022) and concerns about unsound scientific methodology (Baumgaertner, et al, 2018), it is perhaps convenient that improving scientific practices can also boost the public's confidence in science. Thus, reforms in scientific education at the university level, as well as policies to incentivize more rigorous and open practices at the journal and conference level, can be beneficial not just for the quality of our research, but to the public's trust as well. Of course, it is also necessary to *signal* that these practices have been taken up.

Second, the way these practices are described in the media should also be examined. It is notable that in Study 5, peer review status did not significantly impact competence perception, even when comparing a difference of 10% vs. 90% peer-reviewed studies. While peer review is far from perfect (see e.g. Langford & Guzdial, 2015), a body of work with only 10% of studies being peer reviewed should be cause for concern. Thus, I suggest that more attention be paid to educating non-researchers about the mechanics between research, how decisions about research quality are made, and how to competently assess a body of research, in order to help people more effectively and critically engage with scientific information. In addition, this should likely coincide with broader discussions around different models of peer review, whether and/or how appropriate it is to draw from non-peer-reviewed work, and how useful peer review is at all (see e.g. Wang & Zhan, 2019).

Moreover, more attention can be paid to public education here, specifically as it relates to understanding the *process* of doing science in the modern day. In *Why Trust Science*, Oreskes discusses the need to “take to heart—and explain—the social character of science and the role it plays in vetting claims” (2019). An understanding of *how* science gives rise to knowledge is a necessary precondition of trusting that knowledge. Previous research has focused on scientific literacy primarily in two ways. First, in terms of how people understand scientific papers themselves (e.g. Hubbard & Dunbar, 2017)—an important consideration based on my findings from Study 4, as well others’ (Tennant, et al, 2016) that suggest open access articles are an important information source. Second, in terms of public understanding engagement with science (Feinstein 2011) and civic scientific literacy more broadly (Miller, 2016), the ability to understand and appraise scientific developments and become competent outsiders. However, it may be worth thinking about scientific literacy on a more meta-scientific level. There are important signals around credibility (peer review, open data) that non-expert publics could likely use more effectively, if they had a deeper understanding of how they relate to scientific quality.

In a recent study, less than half of undergraduates reported being confident in their understanding of scholarly peer review (Riehle and Hensley, 2017); it should be noted this sample was drawn from research-active undergraduates enrolled in various research symposia, so the full population of undergraduates — and those without college education — almost certainly have less knowledge. Recent policy reports have come to similar conclusions, noting that today’s students cannot (despite popular belief) adequately judge the credibility of scientific sources, with calls to better emphasize *how* scientific knowledge is built (Osborne, et al, 2022). It is no surprise that non-expert publics may not see the full value or nuance of topics like peer review, but given the findings from Study 5, these can act as important credibility signals, so ensuring public understanding of these topics could be a useful way of building credibility of science in the public eye.

Chapter 9

Conclusion

In this dissertation, I have attempted to a) describe why science communication on the participatory web is so important, b) provide insights on how to do it more effectively, and c) guide future research, design, and policy in this space. It is a complex, sometimes extremely challenging problem, but a problem worth solving nonetheless, and this dissertation represents some small progress in doing so. I hope this work can bring us closer to a future where all publics are empowered to access, engage, and use scientific knowledge.

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Appendices

Appendix A: Interview Script for Study 1

Hello! Thank you so much for your time and for volunteering.

- Introduce interviewer names.
 - We are working with professors from the University of Washington, HCDE.
- Research purpose.
 - The goal of this study is to understand HCI researchers' public science outreach learn about the diverse experiences and challenges of the community's members.
 - This will help us gain insights into the specific barriers and limitations of current scientific communication resources.
- Procedure.
 - The interview will last for approximately thirty minutes.
 - All information will be kept confidential except between team members.
 - We may follow up and ask to specifically quote you.
 - You can end your participation in the study at any time without reason.
 - May we record this interview?
 - Questions?
- Questions.
 - Some general questions about your position in research and any things to keep in mind. What is your research field and position?
 - Would you say your practices are typical to most others in your research field? Any extenuating circumstances?
 - Anything else we should keep in mind?
 - Okay, let's begin with some general questions about communication media. In the survey you mentioned that you frequently use [X]. Is that something you still use?
 - How often do you use it?
 - How long have you used it for?
 - Could you describe your recent use of it?
 - Are you happy with what it can do?
 - What is missing from the tool that would make sharing easier?
 - How does this tool help you communicate? Feature-wise?
 - Do you remember why you chose to use this tool over any others? Can you describe your preference in some detail?
 - If you could start again, would you still use the same tool?
 - What do you currently use the tool for? (e.g. Updates on papers, event summaries, interesting tidbits?)
 - (If multiple tools are mentioned) Can you compare and contrast the purposes or functions of the tools you most widely use? What makes you prefer one to another? Do you use both/all, and for what reason?

- Are there any audiences that have been difficult to communicate your research findings with?
- How do you perceive your role as a science communicator?
 - In other words, what do you envision yourself as?
 - Educator? Inspiration?
- What would you most like to communicate with the public?
- Has your perception of science communication changed over the course of your career?
- Who do you collaborate with when projects are done in a lab to review? Could you tell us about your review process?
 - What kinds of audiences do you run your writing by? Who is involved in the process?
 - What is your system of structural review and support?
 - Who's missing from your review process?
- How do you get your work out there and how do you get people to see it?
 - How do you advertise your outreach?
 - How do you judge the success of communication?
 - Do your tools enable you to judge the success?
 - What are the metrics?
- Closing.
 - Do you have any questions for us?
 - Is there anything noteworthy you wish to share?
 - Thank you so much for your time today!

Appendix B: Model development details for Ripple

In this appendix, I describe how we went from data collection to developing our model.

B.1 Data collection

We first identified a representative sample of HCI researchers with Twitter accounts. To include a wide range of HCI sub-communities, we sampled the authors of papers at CHI 2019, a large conference representing an international HCI community that is considered the premier venue for HCI research. We sampled one paper per session, to stratify across different research topics, totalling 184 papers (26.2% of the full 703). These papers had 744 unique authors, and by performing web and Twitter searches, we identified 373 (50.1%) with Twitter handles.

We began collecting tweets on April 1, 2020. By default, the Twitter API provides the most recent 20 tweets on a user's timeline, so our data set included tweets as far back as 2008 for the least active users. We collected this initial set of tweets for a full month, yielding $n = 9011$ tweets. To estimate researcher's downstream audiences, we also needed to collect data on the people retweeting our sample of HCI Tweets; for each unique retweeter ($n = 9965$), we collected their full set of followers (including their user IDs, names, and bios), yielding a set of 11,694,199 total unique Twitter accounts.

B.2 A grounded classification scheme

To develop a classification scheme of Twitter users relevant to HCI science communication, we used a grounded approach beginning with an open coding process. First, we extracted a random set of 50 user profiles from our data, sampling from both our set of HCI researchers' followers as well as the downstream set of users. The first three authors and five research assistants each openly coded this initial set for information in their bios (as well as any LinkedIn pages, professional websites, etc.) that indicated their professional affiliation and proximity to HCI (i.e. what broad audience type they would fall into), and then met to develop an initial code book. Next, we moved on to closed coding, with this group meeting weekly to iterate on the code book and clarify any misunderstandings or difficulties. This process of iteration continued until we had reached sufficient inter-rater reliability (Hallgren, 2012; Krippendorf's $\alpha = 0.70$).

After removing accounts with non-English bios, we were left with a set of 526 profiles. Our initial code book included 13 categories (e.g. researchers, bloggers, educators...). Due to a relatively low proportion in the data, we removed most of these groups from the final scheme. We retained researchers (16.0% of the sample), as one important public for science communication (Burns, et al, 2003). We also retained designers (10.0%), and software developers (20.2%), both due to their large size in the data set, as well as the known research-practice gap that affects these groups (Colusso, et al, 2019); while these are important practitioner groups for HCI, there are communicative barriers between industry and academia, so highlighting the existence or absence of these groups in researchers' Twitter audiences could help identify and bridge some of these gaps. Finally, all other groups were categorized as "other publics" (61.2%). Because many accounts appeared to fall into multiple categories, our coding process allowed for multiple codes assigned to one individual; however, users could only be considered as "other publics" if they contained no other codes (e.g., one could be both a "designer" and "software", but could not be a "designer" and belong to "other publics.").

Because coders were instructed to examine links on the users' bios (e.g. LinkedIn profiles, personal webpages), as well as conduct internet searches on those who provided their full names to identify personal websites, we were able to establish a ground truth data set not seen in prior work in this domain (Barthel, et al, 2015; Côté & Darling, 2018; Kopke, et al, 2019), allowing us to more accurately assess the accuracy of our model (i.e., we can determine if we missed a researcher because their bio did not include information about research).

B.3 Developing the model

While previous research on science communication on Twitter was based on a keyword-matching approach, whereby users were classified as either "in-group" or "out-group" based on the presence of specific keywords in their profiles (Côté & Darling, 2018; Kopke, et al, 2019), past work has suggested that domain expertise among Twitter users can be accurately estimated using topic modeling on their bios (Wagner, et al, 2012). Since we wanted our coded categories to guide the classification model, we opted for a semi-supervised topic modeling approach using correlation explanation (CorEx; Ver Steeg & Galstyan, 2014) with anchor terms (Gallagher, et al, 2017). This approach allowed us to pre-specify a number of topics

and associated anchor terms in order to guide the model toward the categories we had already generated (for a list of topics and associated anchor terms, see Table 7).

To strongly guide the model based on our codes, we set the anchor strength parameter $\alpha = 6$, specifying strong anchors (Gallagher, et al, 2017). We then trained the model on a randomly sampled set of 100,000 user bios from our database (69,426 after removing non-English bios based on the langdetect package for Python). We then tested the model on our ground-truth set of 526 coded bios (see Table B.1). Because past research in this domain did not provide sufficient metrics to fully gauge prediction accuracy (e.g. providing only false-positive rates [Barthel, et al, 2015; Côté & Darling, 2018; Kopke, et al, 2019] without measures of recall/sensitivity), it is difficult to compare our model's success against these methods, as they did not provide more complete measures like F1, balanced accuracy, or AUC. However, our approach performs as well or better than similar methods for classification of Twitter bios for related tasks (e.g. measuring political affiliation (Cohen & Ruths, 2013), profession, or personal attributes (Wagner, et al, 2013)).

Category	Precision	Recall	F1
CorEx			
Researcher	.96	.85	.90
Designer	.92	.91	.91
Software developer	.92	.74	.82
Other publics	.92	.97	.94
LDA			
Researcher	.13	.49	.21
Practitioner	.31	.33	.32
Other publics	.73	.32	.44

Table B.1 Classification accuracy for Twitter user prediction model.

To ensure the efficacy of this semi-supervised approach, we tested this against an LDA model using the same training and test data. We used a scree test (Cattell, 1966) to determine the number of topics ($n = 10$), labeled those topics as either researcher, practitioner, or other, and ran it on our test data. Overall, these categories were less interpretable, and performed less effectively for the purposes of Ripple, than the CorEx approach.

Appendix C: Additional Stopwords for "Who are my audience?"

"unless", "probably", "creates", "un", "awesome", "years", "diego", "prof", "professor", "science", "research", "researcher", "lab", "university", "faculty", "grad", "masters", "data", "design", "designer", "dsg", "user", "experience", "prototype", "https", "views", "opinions", "work", "interested", "candidate", "associate", "phd", "assistant", "studies", "fellow", "scientist", "asst", "assoc", "postdoc", "studying", "researching", "previously", "prev", "like", "former", "formerly", "undergrad", "working", "tweets", "alum", "thing", "things", "ex", "student", "scholar", "new", "member", "enthusiast", "interests", "fan", "de", "el", "nt", "http", "e", "get", "la", "en"

Appendix D: Research-backed tips displayed in the "My Tweets" section of Ripple

Are your tweets reaching the groups you want them to? Here are a few tips to help increase the reach of your tweets:

- Tweet when most of your followers are active.
- Use images when appropriate (Kopke, et al, 2019).
- Use hashtags when appropriate (see "What is my audience talking about?" for examples; Kopke, et al, 2019)
- Make sure your tweets are easily understood by your audience (Tan, et al, 2014)
- Try framing your research to highlight its relevance to your audience (Tan, et al, 2014; Bobkowski, 2015)
- This can involve highlighting its importance or usefulness for your particular audience (Bobkowski, 2015)

Appendix E: Study 4a interview protocol

FAQ for participants: <https://www.cdc.gov/coronavirus/2019-ncov/vaccines/faq.html>

(2 mins) **Facilitator introduction:** Lead and Secondary (Name and affiliation)
After quick intro, Lead kick off into Introduction of what we're trying to accomplish

(3 mins) **Introduction.**

Hello! Thank you so much for agreeing to participate in this workshop. Basically, our goal here is to design a way of summarizing research results regarding COVID-19 vaccines for people in the most useful way possible. We're interested in hearing about a variety of viewpoints, since we want to understand factors around trust and confidence in COVID-19 vaccines

Remember, your participation today is totally voluntary, and if at any point you feel uncomfortable during this session, you can always let me know, skip certain questions, or leave the call entirely. Also, although we may use quotes from this session in a research paper we write about this study, they will be completely anonymized, and you can let us know if you want anything you say here be cut from the record so we don't report on it. We will not release any audio or video from this session.

Pause for questions

Do we have your permission to record this session?

Ground rules:

Facilitator cameras on and want you all to be comfortable on the call so

Participant camera/no camera? (up to participant)

Open discussion – no judgement space, really just trying to gather your perspective

Always ok to skip questions or leave the call

Pause for questions

House keeping:

Mute button – use when not talking

Camera

Pause for questions

(20mins) Preliminary Questions (Q1-2 and Q4-5 Information/source focused. Q3 Hesitance focused)

1. First, I want to ask you some questions about where you've gotten your information about the COVID vaccines. Could you explain where you usually get your information?
 - a. Followup: Have you ever seen information about it on social media?
 - b. Where was that information coming from? For example, news articles, scientific papers?
2. If you were hesitant at any point to get the COVID vaccines, could you explain what made you hesitant?
3. Have you ever read news articles or scientific papers about COVID vaccines?
 - a. Probe 1: Did you intentionally look for the information? What motivated you to access the news article or scientific paper? (did you have a specific question?)
 - b. Probe 2: If not, how did you come across it?
 - c. Probe 3: Did you trust it or not? Why or why not?
 - d. Probe 4: Who wrote it? Was it difficult or easy to understand? Do you have any questions about the article?
4. Do you currently have or have you ever had any questions about COVID vaccines or vaccine research that you wished you had answers to, but couldn't find anywhere?
 - a. [Write down answers so that you can later use them to point out how they are answered in the mockups or not]

(25mins) Feedback about Mockup

Now, I'll show you several mockups of a tool we're planning to build to summarize existing research papers about vaccines. Remember, we're still working on the design and haven't actually built any of it yet, so be completely honest with your feedback.

I should also mention that, even though this is just a mockup, the data we're displaying with it is real, so keep that in mind.

[Show off the mockup(s)]

[Prompt for variables]

Which of these are most relevant to you?

Is there anything missing here that you'd like to know about vaccine research?

[Prompts for each mockup]

Now, I've got a few questions that we can discuss together:

1. "How might this tool help you make decisions about the vaccine?"
2. "What information is missing that could help you make an informed decision?"

3. Is there something about this information/tool that you find misleading or off-putting?

[Additional prompts per mockup, optional]

1. Executive summary
 - a. NA
2. Scatterplot
 - a. Are there any other comparisons that might be useful (other vaccines, other medical interventions)?
 - b. What other information about individual studies would be helpful when deciding whether to trust them?
3. Simulator
 - a. What information would you like about where these simulations are coming from?

[For interaction mockups]

Now, I'm going to show you some different ways we might show you this tool.

[Prompts for each mockup]

1. In what ways would this interaction be useful?
2. In what ways would this be unhelpful?

Sketching Task

For this last activity, I'm going to ask you to sketch out ideas for a tool. Imagine you want to convince your friend to use You can use this online sketchpad if you're on a computer, a physical pen and paper, or anything you have access to. If not, you can also just spend some time thinking about what it might look like, and describe it in words.

I'll give you about 5-6 minutes to roughly sketch something out, and then you can report in and discuss what you came up with.

1. "Could you explain what you came up with?"
2. "Let's discuss how we could combine some of these ideas into something that you would find useful"
3. "How could we integrate this into the social media that you usually use?"

Finale

1. Before we wrap up, do you have anything you want to say that you didn't get a chance to during our session?
2. Do you have any last questions for me?
3. Thank you! [remind how will get your incentive]

Appendix F: Vaccine meta-summary visualizations

Here, I present higher-resolution versions of the meta-summary screenshots from Chapter 6.

Before you read: You've probably heard a lot of messages telling you about COVID-19 vaccines. Of course, you can decide what to do with those messages. We, a group of researchers at the University of Washington, have collected all published papers we could identify by searching for "covid," "vaccine," "side-effects, and "adverse reactions" on Google Scholar up to December 2021, and it's up to you to decide how to use this summary.

Figure F.1. The reactance message used at the beginning of the meta-summary.

Being fully vaccinated and boosted can significantly reduce risk of COVID-19. Notably, scientific studies have shown that the COVID-19 **vaccination reduces risk of hospitalization by about 90%**.

COVID-19 Among the Unvaccinated



COVID-19 Among the Vaccinated



Asymptomatic



Mild-Moderate



Hospitalized



Dead



Long Covid

Figure F.2. The icon array describing the efficacy of the vaccines (used only in the “full version” condition).

25 scientific studies conducted by **20 different research teams** across **15 countries** with more than **63 million participants** have shown that COVID-19 vaccines are safe in general and less risky than the effects of the virus itself.



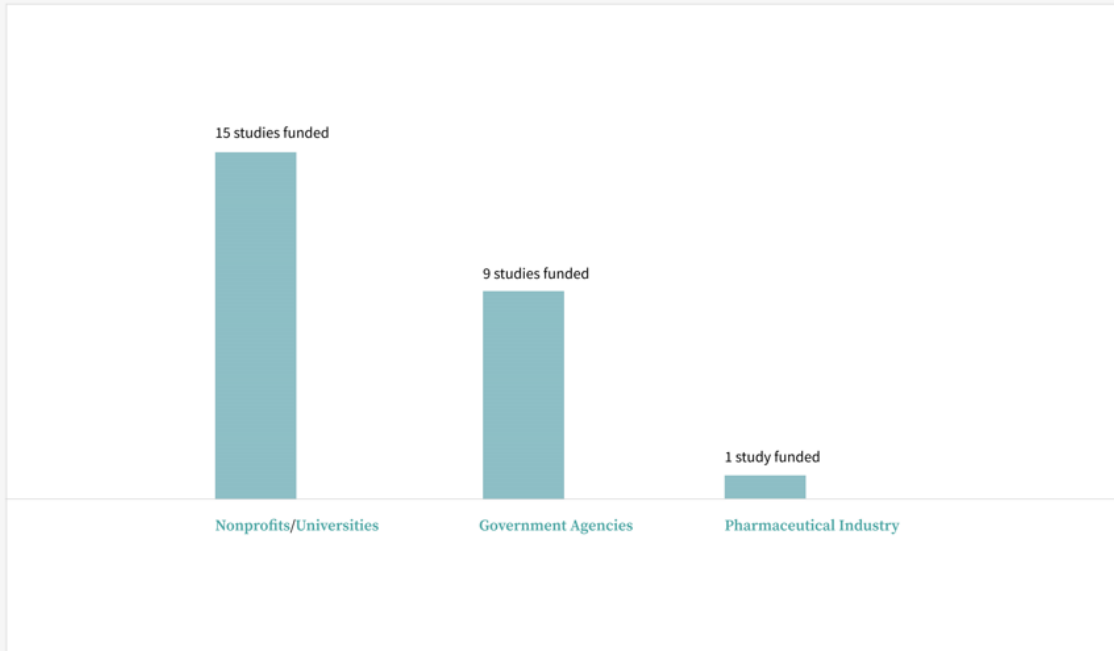
Figure E.3. Bar graph visualizing the number of participants across studies in the meta-summary.

0.0018% of all the participants across 25 scientific studies had an adverse reaction to the vaccine. That's about **1 in 55,000** people. The studies are shown below. Click on each bubble to learn more.



Figure F.4. Interactive graph displaying adverse reaction rates across studies. Users can click each bubble to populate the right-hand panel with information about each study.

Most studies were funded by **Non-profits/Universities (60%)**, while Governments around the world funded 36% of total studies and the Pharamaceutical Industry funded 4% of all studies.



F.5. Bar graph describing the funding sources across studies in the meta-summary.

Appendix G: Sources for meta-science definitions, and synthesized definitions

Peer review

United States Geological Service. (N.D.). What does it mean when a publication is peer reviewed? Retrieved from:

<https://www.usgs.gov/faqs/what-does-it-mean-when-a-publication-peer-reviewed>

Resnik, D. (2011). A troubled tradition. *American Scientist*. Retrieved from:

<https://www.americanscientist.org/article/a-troubled-tradition>

Wiley Author Services. (N.D.). What is peer review? Retrieved from:

<https://authorservices.wiley.com/Reviewers/journal-reviewers/what-is-peer-review/index.html>

Elsevier. (N.D.). What is peer review? Retrieved from:

<https://www.elsevier.com/reviewers/what-is-peer-review>

“Peer review is when experts in a field review a scientific paper before it is published, in order to ensure only high-quality work is accepted. In general, peer review judges a paper based on its originality, importance, and validity.”

Open science/data/materials

Bahlia, C., Bartlett, L., Burgio, K., Fournier, A., Keiser, C., Poisot, T., Whitney, K. (2019). Open Science Isn't Always Open to All Scientists. *American Scientist*. Retrieved from:

<https://www.americanscientist.org/article/open-science-isnt-always-open-to-all-scientists>

The World Bank. (N.D.). Open Data Essentials. Retrieved from:

<http://opendatatoolkit.worldbank.org/en/essentials.html>

Open Data Handbook (N.D.). Open Data Handbook. Retrieved from:

<https://opendatahandbook.org/guide/en/what-is-open-data/>

Open Science Foundation (N.D.). Badges to Acknowledge Open Practices. Retrieved from:

<https://osf.io/tvyxz/wiki/1.%20View%20the%20Badges/>

“Open data means that the researchers have provided their data to be freely used, re-used and redistributed by anyone. It allows other researchers to reproduce their results independently.”

Funding source

Understanding Science (N.D.). Who pays for science? Retrieved from:

<https://undsci.berkeley.edu/who-pays-for-science/>

Stapelberg, T. (2020). Who pays for science? Retrieved from:
https://media.pdx.edu/media/t/1_525g4quy/29662642

Panthagani, K. (2023). Who funds you? Explaining research funding. Retrieved from:
<https://youcanknowthings.com/2023/03/20/who-funds-you-explaining-research-funding/>

Jahnke, A. (2015). Who Picks Up the Tab for Science? Retrieved from:
<https://www.bu.edu/articles/2015/funding-for-scientific-research/>

“Research can require specialized labs, personnel, materials, tools, and money to pay participants. To pay for this, research is usually funded by one of three sources: government, private industry, or non-profit organizations.”