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Seeing the Elephant: Development of a Science Communication Engagement Response Scale

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Seeing the Elephant: Development of a Science Communication Engagement Response Scale

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Dissertation

Presented to the Faculty of the Graduate School of

The University of Texas at Austin

in Partial Fulfillment

of the Requirements

for the Degree of

Doctor of Philosophy

The University of Texas at Austin

May 2021

Dedication

I dedicate this dissertation to my wife, Summer, who provided unending support throughout graduate school. She is the reason I am still in one piece after all this. I also thank the support and guidance from my family who were always supportive and encouraging in my academic endeavor. Finally, I thank my friends who endlessly debate with me about unobservable measurements to help me process scale development whether they know it or not.

Abstract

Seeing the Elephant: Development of a Science Communication Engagement Response Scale

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The University of Texas at Austin, 2021

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Scientists are being called to communicate with the public beyond simple interactions and knowledge transfer. Public engagement with science is now the main outreach method used to increase positive beliefs, favorable attitudes, and behaviors with science. Extant research has outlined key contributors of scientists' willingness to engage with the public, but less is known about the quality of those engagement activities. Relevant theory is outlined in this dissertation through multiple research areas that complete the picture of science communication engagement response. This audience focused variable is then operationalized through scale development procedures that involve item creation, expert interviews, survey distribution, and item factorization. A one factor scale with 12 presents a wholistic engagement measure that demonstrates reliability, content validity, and construct validity. Discussion of intended uses for practitioners and future research follows.

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Chapter I: Introduction

There is an Indian fable about three blind men walking down a path. They abruptly run into an animal they have never encountered before: an elephant. Not knowing what the creature is, they each grab hold of a different part of the animal. Each of the men claims it to be a different animal based on which part they touch. The fable warns against conclusions based on limited experiences and viewpoints. Just as each man only has part of the whole in his head, science communication and engagement has limited its view to the possibility of better-quality engagement. Even though engagement can look different from one context to another, an underlying concept holds it all together. The field of science communication holds on to just one part of the public engagement elephant.

The transition from top-down science communication to more relational communication, or engagement, with audiences is not new. Nearly 20 years ago the CEO of the American Association for the Advancement of Science, Alan Leshner, called for greater engagement and more communication of science to the (2003). This is the leading non-profit organization for scientists in the U.S. and is the world's largest general scientific society with more than 120,000 members ("Mission and History | AAAS," 2018). He suggested scientists and science communicators step away from simple interactions that center on the transference of facts to a more intentional perspective. Numerous studies have described contributors that help explain scientists' public engagement behavior (J. C. Besley, Dudo, Yuan, & Lawrence, 2018; Dudo, 2015; Poliakoff & Webb, 2007). This research has proven fruitful for determining the quantity of engagement, but we do not know what quality science communication engagement looks like when it happens. Even with so many scientists and science communicators looking to improve their interactions with the public, engagement is still nebulously defined and "if [engagement] means everything, then it means nothing" (Johnston & Taylor, 2018).

To fully realize how scientists engage with the public and aid scientists, science communicators, and science communication trainers, this dissertation proposes a measure of Science Communication Engagement Response (SCER) as an evaluation tool for scientists, practitioners, and researchers. SCER is defined as the individual psychological state experienced from a dynamic cognitive, affective, and behavioral interaction through communication about the systematic pursuit of knowledge on a given topic. This dissertation draws a conceptual map that connects disparate literature on engagement from organizational, health, science, and political communication. These domain areas, as described in chapter 1 will represent the theoretical foundation for the measure's subscales and provide unique items in the proposed scale. The second chapter describes the methods, procedures, and results for scale development. This includes qualitative interviews with subject-matter experts and factor analysis of the final scale. Finally, the third chapter elaborates on the findings concerning current research, practice, and future research directions. This dissertation represents the first step toward a possible measure for a science communication engagement scale and a chance to see the elephant and not just its parts.

Chapter II: Literature Review

When someone goes to a museum to see a new exhibit, they're most likely to hear from an expert on whatever topic is displayed. Whether it is a new fossil, artifact, or interactive experience, the exhibit is an outcome of a scientist looking to share their research with interested people. A person might also come across a YouTube video on their lunch break explaining how a new gene-editing technology works or how our universe is expanding. Videos and other media like this can be the product of scientific research built on decades of knowledge. The knowledge that someone spent years studying so you can understand how gene editing like CRISPR works like replacing the teeth on a zipper (Abumrad & Krulwich, 2015), or that a Minecraft world, a popular video game, can be roughly the size of Neptune (Huang, 2012). All of these involve two things, science and effective communication of that science. But it is not enough to relay facts to people (Davies, 2008; Sturgis & Allum, 2004). Scientists who communicate their research with other non-scientists have the added difficulty of converting what they know into engrossing, usable, and engaging topics for the public. Science communication is a growing sub-field in communication research. It has spawned training centers, research initiatives, and a wealth of case studies. However, there is still more to know about the relationship between science and the public. This chapter describes the general science communication model, research, and current measures of science communication engagement. These sections will lay the groundwork for subsequent chapters focusing on constructing a measurement tool for future use in research and science communication training.

SCIENCE COMMUNICATION

Science communication in its broadest perspective is the appropriate skills, activities, or dialogue to produce awareness, appreciation, interest, attitudes, or understanding of science or its processes (Burns, O'Connor, & Stocklmayer, 2003). This definition allows for multiple communicators and multiple audience members or stakeholder groups on the receiving end. Scientists, science journalists or other communicators interested in communicating science can direct communication at various audiences, whether it be the general public, media professionals, policymakers or others. Science communication audiences usually have some prior interest in the subject matter itself. Various publics include anyone who chooses to participate in or receive science communication (McCallie et al., 2009). These public groups have varied backgrounds perspectives, values and life experiences to topics in science communication. Science communication is not a public service announcement for all to stop and listen (Burns & Medvecky, 2018). Science topics can come from science journalists or other media outlets and direct communication from scientists (Gregory & Miller, 1998). There are many reasons for communicating these topics, including dissemination, informing policymakers, or advocating for additional resources. Communicating these topics should ultimately lead to an overall, long-term goal that strategic communication scholars emphasize so that communication activities always remained focused on these goals (J. C. Besley, Dudo, Yuan, & Ghannam, 2016; Hon, 1998). These goals are achieved through scientists' short-term objectives during communication activities like museum presentations, media interviews, blog posts or social media content creation. The way we think about science communication and engagement comes from early reports in the U.K.

about building a more informed society through scientist-public interaction (The Royal Society, 1985), but scientists are increasingly being called upon to engage with the public as a central function of the scientific enterprise (American Association for the Advancement of Science, 2016; Leshner, 2003, 2007). Science engagement goes beyond simple interactions with the public that may foster false conclusions or create negative attitudes. This idea of Public Engagement with Science (PES) has led to a more intentional study of the science of science communication (Scheufele, 2014).

Science Communication Models and Research

The past 20 years of science communication research have wrestled with models that attempt to map out the different ways science and scientists communicate with the public. They start from broad and move to more specific actions and outcomes (Figure 1). At the top is the Public Communication of Science and Technology (PCST). PCST is an umbrella term for most communication about science and incorporates both Public Understanding of Science and Public Engagement with Science. The Public Understanding of Science (PUS) emphasizes strategic communication for science and is narrower than PCST. Finally, Public Engagement with Science (PES) attempts to create a more impactful and longer-lasting interaction than the other two models. These models have progressed and evolved with research that shows how science communication can benefit society (G. Pearson, 2001). The three models are described in detail below, emphasizing theoretical definitions, measurement, and application.

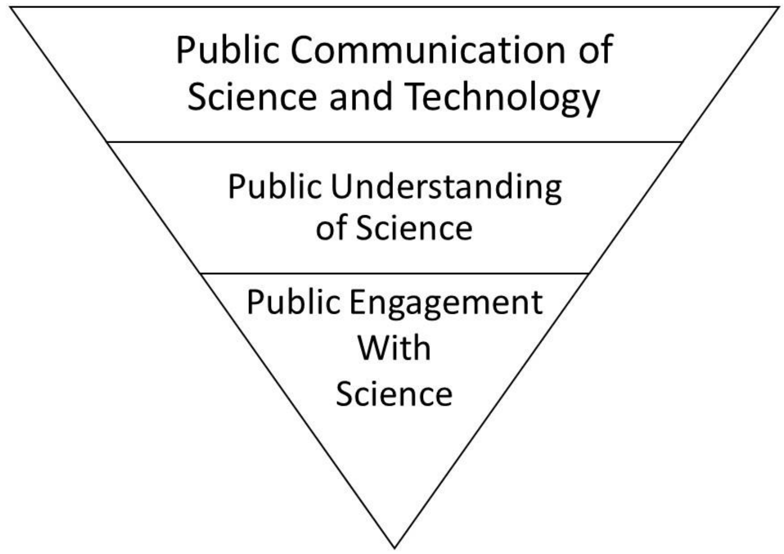

Figure 1: Hierarchy of Science Communication and Engagement Models

Public Communication of Science and Technology.

In 2018 the U.S. National Science Board found data that suggested that Americans have remained relatively positive about science while also becoming more concerned about specific science or technological issues like genetically modified foods, nuclear energy, and climate change (National Science Board, 2018). This concern between science and the public makes science outreach that much more critical. Some issues, such as new technology or elective gene editing, may still cause concern due to uncertainty. But ideally, the public wouldn't be concerned about the entirety of the scientific enterprise. Even though the public sees science in a positive light, little evidence suggests people have sufficient knowledge in scientific issues (Lee, Scheufele, & Lewenstein, 2005; Pew Research Center, 2009). When new technologies appear like nanotechnology, alternative energy, or gene editing, the public response has complicated widespread adoption and has often gravitated around ethical, legal, or social implications (Dean, 2009; Leshner, 2003; Priest, 2008). The role scientists play in aiding these new advancements can expedite or hinder the process of adoption. This isn’t to say that science itself is infallible, but often poor, misguided, or deceptive communication is the crux of negative perceptions of ethical science (Oreskes & Conway, 2011). One way to smooth the sometimes-rigid land between science and society is through effective communication from the scientists themselves.

Public Communication of Science and Technology (PCST) is most often and originally used as a model for effective communication of science between subject matter experts and the public. The public, in this sense, is anyone in society. Burns, O’Connor, and Stocklmayer offer a thorough definition of the term using a handy AEIOU acronym (2003). They define the concept as the use of appropriate skills and dialogue to produce one or more of five personal responses to science: Awareness or familiarity; Enjoyment or other affective response; Interest through voluntary involvement; Opinions that form, reform, or confirm science-related attitude; and Understanding of science and its content, processes, and social factors. These responses may involve a scientist, a mediator, or other members public and can be facilitated through direct interaction or between groups. This definition has guided many research projects aimed at one or more of these responses (Baram-Tsabari & Lewenstein, 2013; Dudo, 2012; Dudo, Kahlor, Abighannam, Lazard, & Liang, 2014; Kahlor et al., 2016). This paper acknowledges that PCST is a purposefully broad concept to help guide science communication research and aid practitioners and science communication trainers. Studies that use this concept include communication with the public when surveying scientists (Baram-Tsabari & Lewenstein, 2013). When studies look into engagement with this model in mind, the overall research goal and application is general communication activity (J. C. Besley et al., 2016; Dudo, 2012).

This term does not, however, emphasize the quality of science messages for the public. Merely communicating with the public does not always produce the AEIOU results that Burns, O'Connor, and Stocklmayer discussed (2003). More must be done for science communication efforts to effectively help public understanding of science advancements.

Public Understanding of Science.

In 1985 the Royal Society and other institutions set up the Committee on Public Understanding of Science (COPUS) to help the Society's new goal on public awareness of science. This committee was eventually dismantled by the Royal Society when they realized that the committee's top-down approach wasn't appropriate for the new millennium's media landscape (Bucchi, 2008b). This top-down model uses a straightforward method for communicating science. Scientists produce original research and then publish it in an academic journal which then a "bridge journal," like Science or Nature, may or may not publish that is more accessible to the general public. These journals would catch the eye of science journalists that would then disseminate the information through their respective media outlets and finally make it into the realm of "popular science." Sometimes information would jump from the top to a communication structure further down the line. This deviation would be limited but force scientists to step in and defend, correct, or direct the conversation (Bucchi, 2008b). These deviations happen more and more with our new media landscape. Because of that, scientists need to be able to disseminate their research to the top journals in their field as well as talk to the general public about their research in a way that makes sense.

Public Understanding of Science (PUS) belongs to one of two broad categories: projects aimed at improving the understanding the public has on an area of science and projects aimed at exploring the public-science interaction (Lewenstein & Brossard, 2006). This model incorporates all different kinds of science and interactions with scientists. Brossard and Lewenstein examine the four sub-models of PUS in their case analysis of different Department of Energy-funded projects related to the Human Genome Project. In their analysis, they use four models commonly discussed in PUS research. The Deficit Model leans on the perception that the public will understand and have a clear outlook on science if the information is available to fill knowledge gaps (The Royal Society, 1985). The Contextual Model is taken from risk communication literature and describes a way of thinking about science according to social and psychological schemas shaped by previous experiences, cultural context, and personal circumstances (National Research Council, 1989; Krimsky & Plough, 1988; Slovic, 1987). The Lay Expertise Model stems from people's knowledge about the world around them from professional, cultural, or community sources that encourage certain opinions about science and science topics (Grove-White, Macnaghten, Mayer, & Wynne, 1997; Wynne & Irwin, 1996). The Public Engagement Model highlights the importance of seeking public input into science issues without necessarily giving control of the content and is often labeled as the dialogue model (House of Lords Select Committee on Science and

Technology, 2000; Sclove, 1995). These sub-models do not fit in neat little boxes, and their borders become fuzzy upon closer examination. Other factors bleed through the lines from one model into the other, as illustrated by Lewenstein & Brossard (2006, p. 33). All models contain the basic function for transferring information from experts to the public. The Lay Expertise and Contextual model both assume audience knowledge about a given topic before or during a communication activity. The Public Engagement model looks to build participation with science and the public and communicate on more even ground similar to how the Lay Expertise model accepts expertise from the audience, and how some communication activities are not just about knowledge transfer but also about changing attitudes like in the Contextual model. Even with this information, the majority of studies still look at what is considered the lower level of engagement: “simple interaction between citizens and scientific experts” (e.g., J. C. Besley, 2014; Dudo & Besley, 2016; Miller & Fahy, 2009; Sardo & Grand, 2016; Yeo, 2015). These simple interactions are a step forward, but only represent the tip of the iceberg for the full potential of engagement. Most studies that attempt to understand scientists’ PUS activity focus on engagement behavior—or more accurately, intended behavior—as their key variable. However, a closer look at this model indicates that not all engagement is created equal.

Public Engagement with Science.

The dictionary definition of engagement mentions occupying, attracting, or involving someone’s interest or attention. Many studies looking at “public engagement” do not set its parameters, or if they do, they offer up a broad definition to suit their research agenda. Some studies even classify engagement as scientists "engaging" with the public (J. C. Besley, 2014; Poliakoff & Webb, 2007). This broad and sweeping definition leans heavily on an understanding of deliberative democracy, a model of communication popularized by political communication scholars. This model focuses on taking control over science from the elite scientists and politicians and giving it to public groups through empowerment and political engagement (Sclove, 1995). Although necessary to examine the overarching area of science communication, this concept still lacks a clear roadmap for researchers interested in future empirical examinations.

At the intersection of political communication and sociology, public engagement consists of three fundamental mechanisms: communication, consultation, and participation (Rowe & Frewer, 2005). This conceptualization emphasizes who is transferring information and who initiates the communication. Public communication is one-way interactions from the sponsor, or the communicators, to the public. Public consultation is information conveyed from the members of the public to the sponsors. Finally, public participation involves exchanging information between members of the sponsors and the public where some degree of dialogue takes place. Communication research often uses public participation as "engagement." However, according to Rowe and Frewer, the combination of communication, consultation, and participation encompasses the entire picture of public engagement. Their typology has provided much of the background into the currently used Public Engagement Model with Science Communication (Brossard & Lewenstein, 2010).

Currently, the most widely used model for science engagement is the Public Engagement Model (House of Lords Select Committee on Science and Technology, 2000; Sclove, 1995). Dialogue is a central focus of this model and links other public engagement areas like public hearings, meetings, and forums (McComas, Arvai, & Besley, 2009). This way of thinking also leans heavily on the public engagement typology expressed above. The sponsor, the science communicator, and the audience communicate back and forth with unset proportions of communication message and feedback (Rowe & Frewer, 2005). This model is used for the majority of studies examined in Appendix A and has been the dominant way of thinking about scientists' communication practices (Bucchi & Saracino, 2016; Gardiner, Sullivan, & Grand, 2018; Nisbet & Scheufele, 2009; Wibeck, 2014; Yuan, Besley, & Dudo, 2019; Yuan et al., 2017). However, the measurement of engagement within these studies does not represent what the model puts forth. Science communication research has used measurements reflecting the general model of PUS or PCST described earlier. Studies that attempt to measure science communication engagement often operationalize it in limited ways, including contact with the media (Dudo et al., 2014), any planned interactions between scientists and non-scientists (J. C. Besley, 2014), or even any activity that engages (Poliakoff & Webb, 2007). These measurements, although appropriate for their respective studies, are restricted and therefore cannot provide greater understanding of the more comprehensive spectrum of engagement.

A handful of studies have begun to operationalize PES activity in ways that complement the theories used in other disciplines or fields. These studies prioritize two-way communication between scientists and the public (Yuan et al., 2017), dialogue-centered communication (Miller & Fahy, 2009), trust and relationship building (Nisbet & Scheufele, 2009; Yuan, Besley, et al., 2019), and community building through public relations strategies (Su, Scheufele, Bell, Brossard, & Xenos, 2017). These studies represent laudable progress, but more focus is needed when it comes to measurement validation and reliability for science engagement. Validity is the practice of making sure the variable of interest is the same one being measured, and reliability is the consistency of measurement between samples (Babbie, 2015). More discussion will follow about the different types of validity and the importance each type for scale development. Readdressing these two pillars of social science theory-building is critical. Until we do, our ability to interpret the data we gather and apply it to science communication stakeholders and scientist communicators is constrained. In sum, science communication researchers need to give increasingly empirical, granular attention to conceptualizing and operationalizing what counts as 'quality' science engagement.

Engagement with science or scientists is a better alternative than the more traditional science communication deficit model. In a deficit model, the scientific community's communication emphasizes transmission of facts and research to fill the knowledge gaps between science and the public (Lewenstein & Brossard, 2006). Once this gap, or deficit, has been filled, the public will be more likely to make choices that reflect the available information. Two decades of Science and Engineering Public Indicators surveys from the National Science Board have demonstrated the lackluster outcomes of deficit model communication (Bauer, Allum, & Miller, 2007; National Science Board, 2018; Sturgis & Allum, 2004). The call for more engagement is one answer to these low numbers of "science literacy." Instead of simple interactions and knowledge transfer, scientists and practitioners are encouraged to engage with the public on a more personal level. The main objectives of PES include exciting others about science, demonstrating expertise, demonstrating community values, framing information, and showing transparency with the scientific process (J. C. Besley, Dudo, & Yuan, 2018). Increasing this engagement comes in many forms and includes intentional, meaningful interactions that provide scientists and members of the public opportunities for mutual learning (American Association for the Advancement of Science, 2016). This form of mutual learning and interaction is also known as two-way communication, or a dialogue model where the public is encouraged to participate in the scientific process and scientists are encouraged to guide them along the way (House of Lords Select Committee on Science and Technology, 2000). Overall, goals for PES are building trust and reinforcing science-related attitudes for improved decision making (J. C. Besley, Dudo, & Yuan, 2018; Braha, 2015).

Current Measures of Science Engagement

Research into the science of science communication has produced fruitful results that can help science communicators develop bonds with key stakeholders (Scheufele & Krause, 2019). The field is growing as science, misinformation, and uncertainty about the future dominate the news cycles and public opinion (Scheufele & Krause, 2019). During the onset of the COVID-19 pandemic, states and large U.S. cities were enacting stay-at-home orders based on the best available evidence from the country's top researchers. Scientists used Twitter to address uncertainty about the coming weeks as the world adopted social distancing procedures to help stop the virus's rapid transmission (Battiston, Kashyap, & Rotondi, 2021; Lai, Wang, Calvano, Raja, & He, 2020). By engaging the public, scientists step down from the public perception of priests of knowledge “uttering eternal truths from the mountaintop of rationality” and offer a chance to discuss their expertise from the front lines of the best available evidence (O’Connor & Weatherall, 2019, p. 44). However, as research continues into what PES looks like, the lack of consistent public engagement measures remains.

As part of preliminary research, this dissertation performed an informal content analysis on published science communication research papers to survey the current conceptualizations and operationalizations of PES. The goal for this informal analysis is to gain perspective of PES studies where engagement is the focal concept. Documenting the definitions, of PES and what models the studies focus on allow for a full picture of engagement in science communication. Citation searches in the journals Science Communication and Public Understanding of Science were conducted for studies with “Public Engagement with Science,” “Public Understanding of Science,” and “Public Communication of Science and Technology” as keywords. From there, any empirical study that used engagement as a focal variable was selected. Previously identified studies found as part of preliminary research for this dissertation not published in those two journals were also included. One last search through published papers that cited the first group of selected studies was performed. There were 26 studies selected from 11 different journals that specifically looked at public engagement as one of their focal variables (see Appendix A). An examination into these 26 studies provided the given definition for each engagement variable in use. The shaded rows represent studies whose definition for engagement reflects two-way or dialogic communication between scientists and various publics to achieve a common goal. This focus on two-way or dialogic communication echoes definitions across multiple key institutions (House of Lords Select

Committee on Science and Technology, 2000; Leshner, 2003; Royal Society, 2006). However, only 9 of 26 studies use a definition in line with these institutions seen as anchors for the field. When studies fail to use this definition, they rely on convenience measures that fit the study's scope and nature. Convenience measures can be beneficial for research on new horizons, but the call for science engagement “in a more open and honest bidirectional dialogue” has been promoted for nearly 2 decades (Leshner, 2003).

There are six noteworthy areas of recent scholarship to consider that help pull the proposed scale into focus. The first two are conceptualizations that are closely aligned with the way this dissertation views public engagement with science. The next two are measurement tools that allow scientists and researchers a better understanding of their intended focal variable. Finally, two evaluation frameworks that specifically look at scientists’ public engagement activity. This collection of recent work is important to consider due to their proximity to the current dissertation. The following paragraphs will outline six papers and provide rationale for why a science communication engagement response scale is needed.

The theory for change introduced by the American Association for the Advancement of Science is a model meant to provide a common language and research-based foundation for various professionals involved in PES activities (2016). This model provides a good starting point for practitioners built on the science of science communication. The theory for change from AAAS outlines public engagement activities through a logic model developed by practitioners. The logic model includes starting points for audience members and potential activities, short and long-term goals for science communicators, and overall vision and outcomes from those goals. This model is helpful for trainers and science communicators alike but does not offer a measurement tool for gauging how much or how little engagement was produced or received. The current scale would be a welcomed tool to incorporate in the logic model for evaluating audience perception of scientists' engagement. Similarly, the U.K. House of Commons Dialogic Model outlines how government organizations can foster positive attitudes with science through two-way communication principles (House of Commons Science and Technology Committee, 2017). This model rests on increasing attitude change of science through recommendations on PES activities, improving the communication of uncertainty and risk, and changing policymaking culture so that dialogue with the public remains a crucial component throughout new projects. Like the AAAS theory for change, it offers no measurement tool to address these dialogic components.

Contrary to the two models above, the DEVISE (Developing, Validation, and Implementing Situational Evaluation Instruments) toolkit from the Cornell Ornithology Lab offers a host of scales and indexes to be used in citizen science engagement (see (http://www.birds.cornell.edu/citscitoolkit/evaluation/instruments). As a major science engagement activity, citizen scientists are used to help researchers with certain aspects of projects (Nisbet & Markowitz, 2015). Although the toolkit contains a scale for participant engagement, the items only focus on behavioral engagement and lack a complete picture of cognitive and affective engagement (Johnston & Taylor, 2018). Finally, the Outcome Expectation Scale for Scientists offers promising validation for measurement tools in science communication research (Peterman, Robertson Evia, Cloyd, & Besley, 2017). The scale measures a latent variable for scientists' outcome expectations for public engagement. Theory linking outcome expectations, or a person's judgments about consequences for a task, posit that positive outcome expectations serve as an incentive for future behavior (Bandura, 2001). This scale is a great measure for response efficacy, a consistent significant predictor of scientists PES activity (Dudo, 2012; Dudo et al., 2018). However, this scale neglects the audience perception of engagement and is a separate tool from the one proposed here. This tool evaluates a scientists' perceived outcome from an engagement activity as it relates to their future activity. This tool assumes that more engagement leads to better engagement. Although that might be true for most scientists or science communicators, scholarship has no way of evaluating the quality of those engagement activities derived from two-way communication theories. The measurement tool developed here will help evaluate engagement activity, not just the tendency to participate.

Finally, two recent evaluation frameworks for evaluating science communication training have been published that offer sound research on comprehensive training programs for science engagement. Stylinski, Storksdieck, Canzoneri, Klein, and Johnson looked at public engagement training through the Portal to the Public training model 2018). This program, meant for science centers, seeks to connect the public with community research initiatives through engagement activities and dialogue with local scientists. It represents a robust framework that many science communicators see success with. Their study looks at the impacts from such a strong training program and found that scientists who took part in training pursued more hands-on engagement and conducted more outreach than those who had not participated. Similarly, Rodgers et al. have developed a training program of their own through funding from the National Science Foundation (Rodgers et al., 2018). Their Decoding Science framework for evaluating science communication training improved trainee's communication self-efficacy, oral presentation self-efficacy, and perceived science communication knowledge as well as audience scores for attitudes, perceived credibility, affect, involvement, and behavioral intentions. This framework represents another advancement in science communication training. However, these two studies do not offer theoretically sound validation tools for public engagement with science and instead offer programs and outlines for training programs. This may seem like one in the same, but engagement is not what you want it to be no matter the context. Engagement has set thresholds to bridge from broad communication interactions to two-way, dialogic communication where proportional feedback is exchanged (Johnston & Taylor, 2018; Rowe & Frewer, 2005). The scale developed in this dissertation would benefit both of these frameworks if PES is to be evaluated fully. Self-efficacy in science communication is important, but just because a scientist is a confident public speaker does not improve their public engagement. Audience members will be more engaged if theoretical understanding of communication engagement is incorporated into the examples above.

The current study addresses the gap in measurement that these models and scales do not fill. For engagement to be measured, science communication scholars, practitioners, and trainers need a tool to represent the quality of engagement activities. Given the current communication engagement literature, this proposal draws on a handful of multidisciplinary theoretical foundations for suggested components of a Science Communication Engagement Response scale. The proposed scale will help address quality engagement from the eye of the beholder, the audience, for an accurate measure of the construct and would be a significant step in explicating the term for science communication scholars.

Chapter III: Theoretical Foundation

COMPONENTS OF SCIENCE COMMUNICATION ENGAGEMENT

Scale development has many steps. The first step is to conduct a meaning analysis, which entails describing a construct's conceptualization. Properly describing the linkages from the construct to its theorized components and dimensions is an essential first step of the development process. This chapter outlines the major components and theoretical dimensions of the concept, science communication engagement. First, I describe applicable theories connecting the latent variable to its components. Then I describe the potential factor structure and underlying dimensions, followed by the construction of scale items.

Communication Engagement

Engagement in its broadest conceptualization is the psychological and behavioral attributes of connection, interaction, participation, and involvement designed to achieve or elicit an outcome at individual, organizational, or social levels (Johnston & Taylor, 2018). This definition places engagement at a critical part of democracy, offering a conduit of voice, representation, and collective-level influence for decision-making (Ryfe, 2016). The major outcomes from deliberative engagement include informed opinions, attitude changes, and increased trust (PytlikZillig, Hutchens, Muhlberger, Gonzalez, & Tomkins, 2018). Science communication literature echoes these outcomes as the impetus for increased PES (American Association for the Advancement of Science, 2016; J. C. Besley, Dudo, & Storksdieck, 2015; Bucchi, 2008a; Davies, 2010; Scheufele, 2014; Wibeck, 2014). According to Johnston and Taylor (2018), communication engagement breaks down into four dimensions, where the focus is on an individual or social level and as a state or process. These four dimensions (individual state, individual process, social state, and social process) all lead to creating an idealized society that starts with individuals experiencing an engaged state. Although idealistic in its outlook, this model offers good insight into how the outcomes mentioned above can be achieved (Figure 2).

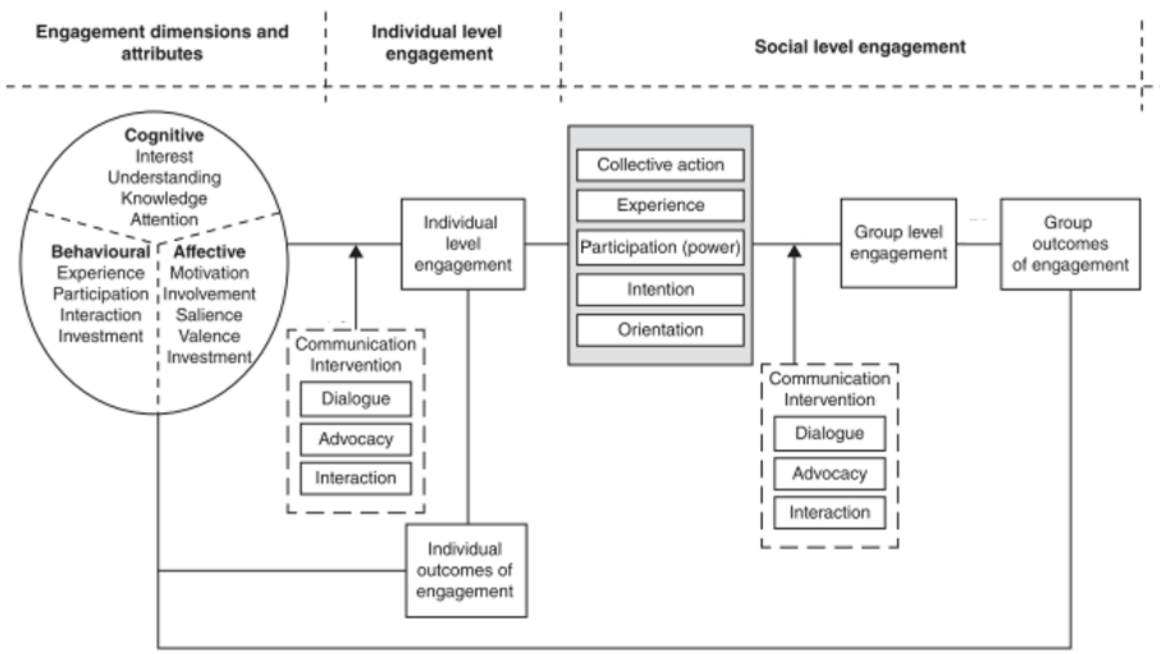

Figure 2: Multilevel Model of Communication Engagement developed by Johnston & Taylor, 2018 (p.29)

At the individual level, engagement includes cognitive, affective, and behavioral dimensions (Fredricks, Blumenfeld, & Paris, 2004). Cognitive engagement is described as attention, processing, or thinking skills to develop understanding or knowledge. This engagement dimension would include being immersed or interested in a topic and a willingness to spend time and effort to comprehend complex ideas or master difficult skills. Sometimes described as a loss of time during an interaction, cognitive absorption occurs when an individual is fully immersed in a topic (Agarwal & Karahanna, 2000). Activities or information that results in high cognitive absorption produces higher cognitive engagement levels (Oh & Sundar, 2015). This is different than a flow state. Flow states arise when activities are intrinsically enjoyable and represent a challenge to an acquired skill (Csikszentmihalyi, Abuhamdeh, & Nakamura, 1990; Jackson & Marsh, 1996). In either case, the cognitive dimension of engagement emerges and pulls the individual forward toward individual state engagement.

Affective engagement encompasses positive and negative emotional reactions like enjoyment, fear, anger, support, and belonging. These emotions, depending on the valence, can induce an attraction or repulsion for a topic. Positive affective engagement promotes an individual's motivation, interest, or concern. Negative affective engagement would decrease these reactions to PES activities. Emotions play a large part in what messages people engage with. Negative emotions tend to decrease persuasive messages from quitting smoking (Smith & Stutts, 2003) to climate change communication (O'Neill & Nicholson-Cole, 2009). Affective reactivity, or how someone responds to emotional messaging, determines how health (Zillmann, 2006) and news (Gibson, Callison, & Zillmann, 2011) information is received and called from memory. Messages with more emotional language have longer-lasting effects and are easier to recall from memory (Zillmann, 1999).

Finally, behavioral engagement includes concepts of participation, collaboration, action, and involvement. These behaviors build upon affective or cognitive engagement or act as the starting point for engagement (e.g., when a scientist invites someone to join in on a demonstration). Measurement of this dimension is often through superficial digital interaction metrics such as “likes” on Facebook or “favorites” on Twitter (Yeo, 2015; Young, Tully, & Dalrymple, 2018). However, recent research to operationalize behavioral engagement presents specific components for higher quality digital engagement (J. Oh, Lim, Copple, & Chadraba, 2018; Jeeyun Oh, Bellur, & Sundar, 2018). Digital engagement is only one side of the behavioral engagement coin. Face-to-face or direct engagement is just as powerful for enhancing cognitive and affective components. Science festivals, for example, have been shown to promote greater enjoyment of science and help bridge the gap between science and the public (Sardo & Grand, 2016).

These three dimensions make up individual state engagement and lead into individual engagement as a process, social state, and social process (Johnston & Taylor, 2018). Individual state engagement is the most appropriate level to focus on for the current measurement tool. The proposed Science Communication Engagement Response scale measures how an individual feels soon after interacting with a scientist or other science communicator. Besides calls for more research on quality PES, the current measurement tool also acknowledges similar calls from public relations and organizational communication scholars, discussed next. The proposed scale will further our understanding of the chain of events from individual state engagement to building social capital that then flow into ideas about deliberative democracy (Johnston & Taylor, 2018; PytlikZillig et al., 2018).

Dialogic Communication

Public relations scholars define public engagement through dialogue with scientists and non-scientists (Bauer & Jensen, 2011). Dialogue is more than just simply talking to another person, and so to help scientists engage, trainers must know the difference between good and bad dialogue. Dialogue is defined as communication with an orientation to the other person that recognizes that person's self-worth and is inherently ethical (Pearson, 1989). This conceptualization sees dialogue through the I-Thou relationship where communicators view other parties as equally human (Buber, 2012). The alternative, monologue, is categorized through the I-It relationship emphasizing separateness and detachment. These concepts draw a direct comparison between the shift from deficit model thinking to PES models of science communication. Instead of talking at publics, scientists are encouraged to engage with interested audiences to promote attitude change. Dialogic Communication theory proposes that engagement through this lens recognizes the other person as an equal and not through a hierarchy (Taylor & Kent, 2014). When communicators, in our case scientists, commit to this dialogic communication style, their audience will feel valued as the human beings they are and not as a strategic resource. This style of communication theorized in the public relations literature requires audience or public input, experience, and needs and prioritize interactions outside of immediate need from the scientist (Young et al., 2018). Taylor and Kent describe engagement as always including intentional dialogue. Although not every online conversation between a scientist and a non-scientist is dialogic (Twitter likes, comments on Facebook, Blog post sharing), every dialogic interaction contains conversational engagement.

Taylor and Kent offer five components of engagement through dialogic communication. First, engagement requires interactions with stakeholders/publics to begin only after secondary research has been conducted. This can help scientists understand vital issues, publics, and cultural variables closely tied with Contextual Model (Lewenstein & Brossard, 2006). Secondary research for stakeholders/publics can include simple acknowledgement of the audience demographics a scientist interacts with or past legislative behavior for an upcoming meeting with policymakers. The second requirement is to demonstrate positive regard for stakeholders/public input, experience, and needs. Engagement cannot be disingenuous, and scientists must show that they care for their audience for high-quality engagement. Because some recent evidence suggests that Americans commonly regard scientists as being cold (Fiske & Dupree, 2014), this component may be essential for quality engagement. Demonstrating positive regard is essential to two-way communication where scientists assume positive intent from their audience. Showing concern about issues relevant to specific communities is an easy tactic that can help scientists meet this dialogic requirement. The third component is maintaining interactions with stakeholders/publics outside of an immediate issue or problem for engagement to happen. Scientists who only communicate with the public in times of their own need will limit their ability to create quality engagement. Maintaining an active voice online when you don't have specific research to promote can build social capital with an audience for future times of need like when the Center for Disease Control (CDC) held a virtual open house about the Zika (Dalrymple, Young, & Tully, 2016) and Ebola viruses (Lazard, Scheinfeld, Bernhardt, Wilcox, & Suran, 2015). The fourth requirement is that interactions with stakeholders/public should ask for feedback on public or community concerns. These interactions can include scientists asking the public about issues like climate change mitigation or gene editing technology. Questions about uncertainty in science can open up discussion about how science is done and when scientists are comfortable saying there is “proof” of something. Whether or not a scientist has any say in topics their audience deems important is entirely up to the organizational structure they are under, but these interactions are still important for dialogic engagement. Finally, Taylor and Kent propose that engagement requires interactions that contribute to a fully functioning society whereby organizations and publics recognize their interdependence and act together for the community's good. This is a somewhat unclear requirement from Taylor and Kent, but scientists often see themselves as helping society in general with their research, which is also a contributor to their willingness to engage (Poliakoff & Webb, 2007). This property of dialogic engagement may be easier for science communicators to perform as they are often drawn to communication that helps society (Dudo & Besley, 2016).

Organizational communication has focused on dialogic communication for some time (Kent & Taylor, 2002). The focus stems from organizations' move to shift power in favor of the various stakeholders involved in the organization (Taylor & Kent, 2014). This conceptualization was formally operationalized in a scale for Organization-Public Dialogic Communication (OPDC) (Yang, Kang, & Cha, 2015). The OPDC scale includes two factors for good dialogue: mutuality and openness. Mutuality refers to the mutual confirmation of different viewpoints brought by each communicator, and openness is the communicator's ability to be transparent, genuine, and accessible. These engagement requirements in dialogic communication help build a foundation for how the public sees engagement from organizations. Taylor and Kent note how this can translate from an organizational perspective to an individual perspective for building up good public relations among stakeholder groups or publics (2014). A dialogic communicator, in their view, comes into an interaction with their own beliefs, values, and attitudes. Scientists should have their own goals and objectives for communicating, but they should also enter into communication open and ready to change. Having a transformative empathic mindset may provide another way in which scientists can engage and produce engaging interactions with their audiences.

Empathy

There does not seem to be a shared definition of what constitutes empathy. The common definition is the ability to put yourself in another person's shoes. Different scholars have proposed different conceptualizations of empathy. This section offers two perspectives, both with a multidimensional view of the concept. The first looks at empathy from a sociological perspective and the second leans on psychological properties that help motivate and suppress empathic behavior.

Feeling for another individual means that one's worldview, or what Nelems describes as a "canopy of meaning," acts as a reference point and is hard to do when someone categorizes the Other as "very distant." Nelems suggests that this definition is too narrow and is inherently individualistic in its parameters (2017). Instead, Nelems and others offer a multidimensional approach. This conceptualization borrows from Boler's passive and transformative empathy model as one pole or axis (1997). The passive categorization of empathy results in no change regarding the Self or the Other's orientation besides a temporary, fleeting experience. Passive empathy is the individualistic conceptualization of stepping into another person’s shoes. The Self is still in control of the situation and metaphorically removes the Other from their feelings. This perspective draws on one’s own beliefs, assumptions, and worldviews and can often result in pity or care for the Other based on fear for the Self. The transformative perspective of empathy is self-reflection and a willingness to part with one’s worldview to encounter the Other. The distinction between the two categories lies within the extent that the Other must remain intact while the Self opens themselves up to potential changes. Nelems describes this type of empathy as the Other staying in their shoes.

Another dominant perspective describes empathy containing three main components. These include mentalizing, experience sharing, and mind perception (Zaki, 2019). Mentalizing is the observer's capacity to draw explicit inferences about targets’ intentions, beliefs, and emotions (this is the Self in Nelems conceptualization), Experience sharing is an observers’ tendency to take on the sensory, motor, visceral, and affective states they encounter in targets. Finally, mind perception is the observers’ detection of the target’s internal states. This perspective also posits that empathy is both automatic and context-dependent based on approach and avoidance mechanisms. An affiliation mechanism may explain why some people empathize with groups to strengthen social bonds while avoiding empathy could be caused by the perceived pain of sharing another person's emotions (Zaki, 2014).

Although concepts surrounding empathic behavior have been examined like scientists’ communication objectives of hearing what others think and demonstrating community care (J. C. Besley, Dudo, & Yuan, 2018), there has been little to no research on how the public might perceive a scientist's empathy toward them. One study found that polite scientist communication style was less persuasive in an article about genetically modified food compared to a more aggressive and assertive condition (Yuan, Ma, & Besley, 2019). This study presents some interesting comparisons to the idea that scientists should communicate a warm and friendly tone with audiences. One explanation for this could be in the context and ultimate goals the scientist has. Persuasive and risk communication styles might encourage a more assertive tone with publics to change behavior, but for scientists who demonstrate audience care through dialogue generate more positive attitudes with audience members (Zorn, Roper, Weaver, & Rigby, 2012). A multidimensional scale for empathy that looks at how perceived emotional connections with scientists is helpful hereto better measure science communication engagement. One commonly used scale for empathy includes dimensions of empathic concern and perspective taking(Davis, 1983b). These areas are similar to Zaki's dimensions for mentalizing and experience sharing. This scale previously helped explain how higher empathy individuals were more likely to stay on a web page with science information (Knobloch-Westerwick, Johnson, Silver, & Westerwick, 2015). The proposed scale incorporates the multidimensionality of empathy for science communication engagement.

Interactive Engagement

When calls for more science engagement began, the main option was direct community involvement through museum activities and other science centers. In the past decade digital media and social networking systems have competed with those in-person engagement activities so that it's now much easier for scientists to reach audiences online. The changing media ecosystem and digital migration due to COVID-19 make digital communication an important part of any scientist's engagement activities. With this in mind, it is not surprising that scientists increasingly take to social media, blogging, and other online sources to discuss their research and other science issues (Howell, Nepper, Brossard, Xenos, & Scheufele, 2019; Stevens, Mills, & Kuchel, 2019; Yeo, 2015). Interactive media permeates these new communication channels for scientists, and how users engage with content on websites can be measured through digital engagement models beyond just likes and shares (Jeeyun Oh et al., 2018). This research helps illuminate digital user engagement and offers science communication scholars a framework to build on for engagement online. As such I take advantage of this previous work and build it into the conceptualization of science communication engagement.

The user engagement model of interactive media contains four component variables that lie on a continuum of engagement: interface assessment, physical interaction, absorption, and digital outreach (Oh, Bellur, & Sundar, 2018). The first is seen as a user's first interaction with online media before they can cognitively engage with the content. Interface assessment is the novel attraction to an online media interface and its ability to initiate and maintain an active user interaction. Visual features, aesthetic appeal, perceived usability, and so on are likely to draw the user in or not before they get to the interface's content. A second component variable is physical interaction with the interface. These are the tangible ways a user can interact with an interface. In this model, the physical ways a person uses an interface are equal to their assessment of that interface. Physical interaction and interface assessment then impact the last two components in the model sequentially. Absorption is the experience of temporal disassociation, focused immersion, heightened enjoyment, curiosity, and control over a computer interaction (Agarwal & Karahanna, 2000). This definition is connected to engagement, absorption, and transportation by different scholars but equally measure each of these phenomena (Slater & Rouner, 2002). Finally, the authors list a component of outcome behavior seen as the active organization of content in which a user was absorbed. This sharing and exchanging of content is integral to the user engagement experience and represents the last chain of events in their model.

Science communication can lean on this model to maximize communication online. Some components in the model can't be directly modified like the interface or physical interaction from the user. However, these are still important digital features to consider when using a preexisting platform. Absorption and digital outreach are encouraged for science communication. Content that creates heightened enjoyment, curiosity and immersion can increase later deliberative discussions from users (Dubovi & Tabak, 2021). Those discussions can come from sharing or other features that allow users to catalog content for future consumption sharing. This digital engagement feature is important for scientists to consider when thinking about overall public engagement because it can help increase two-way communication online (Su et al., 2017)

The digital space is overtaking face-to-face engagement in science communication, but not all engagement is behind a screen. Physical interaction with scientists can be equally rewarding for science-curious individuals. One study looked at audience participation and engagement during a science summer festival and found that audiences seek events that encourage them to ask questions, converse, and talk through opinions (Sardo & Grand, 2016). In general, science festival attendees leave with greater interests and curiosity about science (Jensen & Buckley, 2014). These experiences are much more impactful per engagement activity due to their potential for people to meet with and talk to scientists. Other variables like participating in scientific demonstrations can only improve these interactions, especially when scientists demonstrate previous components (Bultitude, 2014). In sum, maximizing dialogic communication, empathic connection, and meaningful interactions—both virtual and personal—could likely boost the quality of science engagement efforts.

Science Communication Objectives

One way scientists can optimize their communication efforts is through strategic communication principles. Ideas about communication toward an overall goal have been studied in public relations (Hon, 1998) and health communication (Rice & Atkin, 2013) for some time. This same strategy can be used for scientists to map out their communication activities. Scientists should have clear long-term goals and short-term objectives for their communication efforts. Goals are long-term desired communication outcomes often a behavior sought by the scientists for their audience. Scientists should then think through shorter-term objectives that may help meet this goal and then use specific communication tactics to help them achieve the short-term objective (Grunig & Repper, 1992). Focus on two-way symmetrical communication is important for goal, objective, tactic structure through meaningful dialogue (Linda Childers Hon et al., 1999) for high-quality communication in public relations and other strategic communication fields, including political science (Carpini, Cook, & Jacobs, 2004) and heath communication (Rice & Atkin, 2013). Research that brings this goal-objective-tactic structure has seen success in determining how often scientists communicate and what goals they prioritize when they communicate (J. C. Besley et al., 2016; Dudo & Besley, 2016). These objectives offer a connection to core science communication outcomes with the previous areas of engagement to provide a better picture of science communication engagement.

There are many communication objectives that scientists prioritize as well as overlook. The objective of increasing knowledge continues to be a top priority for scientists (Bauer et al., 2007; J. C. Besley & Nisbet, 2013; Dudo & Besley, 2016). Scientists also continue to promote the idea that increasing public knowledge about scientific facts and processes substantially increases public support for science despite the lack of evidence for this “deficit model” (Bauer et al., 2007; J. C. Besley & Nisbet, 2013; Dozier & Ehling, 1992; Fischhoff, 1995). Other non-informing objectives are prioritized less by scientists, such as fostering interest in science, building trust, framing issues to resonate with audiences, and a handful of others that influence scientists’ willingness to engage (J. C. Besley et al., 2015; Dudo & Besley, 2016). These attitude objectives focused on attitude and not information also contribute to audience engagement with science communication because of their short-term nature. Scientists and researchers deem these objectives necessary for building up positive beliefs in science. Informing others about science is often a part of every science communication activity and is a prerequisite for labeling communication as science communication. Scientists and science communicators often share information when issues arise. However, if scientists want to increase their engagement, a dialogic model recommends this even outside of immediate problems.

Scientists often prioritize communication that seeks to excite or interest. This idea of novelty between the audience and the content should help increase science communication engagement. What information is novel and what is not depends on the scientists' audience and their expertise. Science communicators can use pop-culture trends to craft topically similar content, such as a parody rap song about antibodies (Baxter, 2019). Additionally, framing science information can aid in creating novelty for audience members. Framing shows an issue in different ways or tailoring research findings for a specific audience (Nisbet, 2010). Framing inherently improves accessibility and resonance with science. Using existing analogies known to an audience will help improve cognitive engagement by connecting the dots between existing and new information.

Demonstrating trust in science or scientists is also a worthy science communication objective. To do this, scientists have to show that they have integrity and benevolence towards their audience. Benevolence ties into similar structures in dialogic communication, such as grounding, where the speaker/organization tries to establish common ground with the audience/public. Another science communication objective closely paired with demonstrating trust is demonstrating that scientists are experts in their field. The public often sees scientists as "priests of knowledge," so sometimes expertise is shown already. When a science audience doesn't perceive a communicator as an expert, scientists must establish content expertise to gain trust. One helpful tool is the Muenster Epistemic Trustworthiness Index (MEDI). This collection of questions measures judgments people have when deciding whether to trust an expert to bridge an informational gap (Hendriks, Kienhues, & Bromme, 2015). Scientists can demonstrate trust and expertise by presenting themselves as competent and professional, sincere and honest, and moral and ethical. These judgments from the audience will help inch the scientists further into higher quality engagement than if they neglected them.

Additionally, science communication objectives can also inform how scientists can be more transparent and attentive to audiences. Asking what the public thinks can offer an olive branch between the expert and the public. Through dialogic theory, presenting yourself as attentive and caring about what the audience has to say can demonstrate greater grounding. Discussing science issues play a central role in the perceptions of voice on decision making (J. C. Besley et al., 2017; Lind, Kanfer, & Earley, 1990). With more perceived say in an issue, members of the public can feel more positive beliefs in science. Demonstrating transparency as a communication objective is also critical for science communication engagement. Replication is central to the scientific method, and the same principle can also increase communication engagement. By peeling back the curtain on science, scientists can invite members of the public to a world they only see from the outside. Social media trends like #OverlyHonestMethods and #FieldworkFail allow the public to participate in these private conversations about how science works (Simis-Wilkinson et al., 2018). Examples like these shows how transparency can build higher-quality forms of engagement through dialogic methods. Finally, two science communication objectives focused on scientists demonstrating community and social values. These objectives center on warmth or benevolence on behalf of the scientific community. They also tie into empathy perspectives (Nelems, 2017) and dialogic communication (Taylor & Kent, 2014). Both feeling for and feeling with community members results in more positive attitudes about science and scientists.

Demonstrating altruistic values towards others can also build up perceptions of epistemic trustworthiness through integrity and benevolence. Scientists who show that they care can improve their engagement activities with audience members.

These objectives and others described here create a link between existing theory in dialogic communication, empathy and digital engagement to science communication. The structure of these ties displays heavy crossover from one concept to another. A scale with a seven-factor structure based on twelve dimensions from the theory linkages above can help realize this a latent variable for science communication engagement. The first area is the recent work done to measure organization-public dialogic communication based on dialogic theory (Taylor & Kent, 2014; Yang et al., 2015). The second area is the work done on epistemic trustworthiness (Hendriks et al., 2015). This previously validated scale blends into key areas of science communication objectives like establishing expertise and trust. Then, foundational research into scientists communication objectives that go beyond knowledge transfer (J. C. Besley, Dudo, & Yuan, 2018; Dudo & Besley, 2016; Yuan, Besley, et al., 2019) is used to connect existing scales to current ideas of PES. The final area includes digital and behavioral engagement research (Johnston & Taylor, 2018; Jeeyun Oh et al., 2018; PytlikZillig et al., 2018). These research areas provide connections to form a web of multidisciplinary conceptual linkages that form the basis of item creation for a scale of science communication engagement response. The following section goes through each area and provides descriptions of the potential factors.

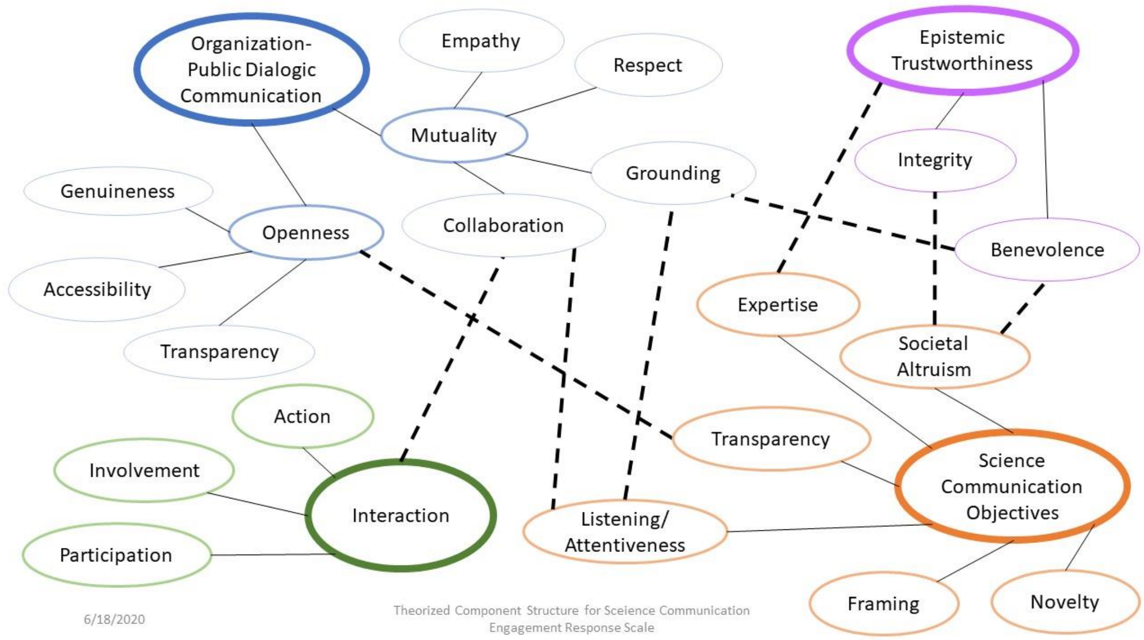

Figure 3: Theoretical linkages of Science Communication Engagement dimensions. Solid lines indicate connections made through previous literature. Dashed lines represent connections between different areas of research for science communication engagement.

POTENTIAL FACTORS OF THE LATENT VARIABLE

The PES model positions higher quality engagement with the public as a product of dialogue or two-way communication (Davies, 2010; Yuan et al., 2017; Zorn et al., 2012). Better dialogue and relationships with the public is operationalized in only a handful of science communication studies (Kurath & Gisler, 2009; Young et al., 2018; Yuan et al., 2017). Still, this small handful often measures the same concept in different ways. When research does not use dialogue or two-way communication as engagement variable, they have limited scope and often overlook research done in other disciplines and fields. This section outlines a scale for Science Communication Engagement

Response (SCER), or the individual psychological state experienced from a dynamic cognitive, affective, and behavioral interaction through communication about the systematic pursuit of knowledge on a given topic. Each of the next sub-sections will describe the potential factors.

Mutuality

Mutuality is a function of dialogic communication and includes ideas of empathy, respect, grounding, and collaboration (Yang et al., 2015). These dimensions, along with empathy, round out the mutual orientation to other communicators for support, sharing commonalities, and looking for the same outcomes. The science communication literature has labeled these concepts as key objectives scientists should be thinking about when communicating (J. C. Besley, Dudo, & Yuan, 2018). These objectives contribute to more meaningful, long-term goals. When scientists communicate with the public, hearing what others think about science can lead to better perceptions of science decision-making (Besley and McComas, 2015). Science communication objectives that feature the idea of mutuality focus on community values. Scientists can demonstrate how they share values and want to achieve similar outcomes for communities (L. F. Davis, Ramírez-Andreotta, & Buxner, 2020). Empathy plays a large part in the current training for science communication. The Alan Alda Center for Communicating Science focuses its training on improvisational acting techniques for learning how to read your audience Alda (Alda, 2018). This reading comes from the ability to both interpret and demonstrate empathy (Kaplan-Liss et al., 2018). Empathy has deep roots in psychology research and measures one's ability to take perspectives and concern for others (Batchelder, Brosnan, & Ashwin, 2017; M. H. Davis, 1983a). A motivated model for empathy looks at the concept from decisions made to approach or avoid the behavior (Zaki, 2014). This model breaks the concept down into three subgroups. Experience sharing describes how people vicariously take on emotions observed in others. Mentalizing describes how people gather information about someone’s behaviors and situation to deduce how they feel. Finally, someone can also demonstrate empathic concern where they wish for people to feel better and even go about ways and plans to help. Zaki’s conceptualization is the most current and compelling, and this proposal will use it for the empathy component (2014).

Openness

The second dimension of dialogue is a communicator's ability to provide a climate of openness to their audience (Yang et al., 2015). Genuineness, accessibility, and transparency reinforce the idea that when organizations are open to honest communication, their audience can engage better with topics and issues. Similar concepts exist in science communication objectives where demonstrating transparent and open ideas about the scientific process can lead to more positive attitudes about science (J. C. Besley, Dudo, & Yuan, 2018). Openness is also one of the objectives that scientists prioritize most when engaging the public (Dudo & Besley, 2016). It is considered an essential attribute of engagement where equal access for all parties is necessary for symmetrical communication (Habermas, 1984) and informational fairness ideas (McComas et al., 2009).

Epistemic Trustworthiness

The determined expertise or credibility of a science communicator is a necessary component of engagement. Positive ideas of scientists' credibility promote more favorable evaluations of the usefulness, accuracy, and objectivity of science perceptions, where negative perceptions result in questioning motives, capabilities, and judgments (Hartman, Dieckmann, Sprenger, Stastny, & DeMarree, 2017). There's also evidence that suggests the correction of misinformation is better received depending on the source's credibility (Vraga & Bode, 2017). Scientists also prioritize demonstrating their own or the scientific community's expertise when communicating to the public (Dudo & Besley, 2016). The Muenster Epistemic Trustworthiness Index (METI) can add to the current understanding of expertise and credibility (Hendriks et al., 2015). This scale measures laypeople or non-expert audiences' trust in experts. This measurement tool demonstrates how expertise, integrity, and benevolence make up an audience's epistemic trustworthiness. This trustworthiness focuses on experts' features that determine how non-experts will depend on and defer to them for beliefs about science issues. Benevolence in this scale looks at scientists' ability to demonstrate ethical practices, moral decisions, responsibility, and considering others. This is closely aligned with the next potential component for science communication engagement.

Altruism

Altruism, or the quality of being a well-meaning individual or showing general kindness, is derived from another science communication objective (SCO) as well as ideas about benevolence described above. Generally, scientists prioritize this objective for public engagement (Dudo & Besley, 2016), and science communication trainers see this as valuable (J. C. Besley et al., 2016). Showing that you care about society's well-being is also a good indicator of communicating trust and other fairness research in interpersonal communication (Fiske & Dupree, 2014; McComas et al., 2009). Scientists are also more likely to engage with the public if they see public engagement as beneficial to society (Peterman et al., 2017; Poliakoff & Webb, 2007). These findings make altruism a possible factor for the hypothesized latent variable.

Framing

Communicating science can be complicated due to the complexity of information. Describing science in a more interpretable way that makes sense to an audience with relevant schemas is one way to get around this inherent complexity. Framing science, although prioritized least as a science communication objective (Dudo & Besley, 2016), can help recontextualize science so that it resonates with existing values (J. C. Besley, Dudo, & Yuan, 2018). Framing science in different ways can also shape outcomes like positive attitudes and future behavior (Myers et al., 2012). Comparing a topic to something an audience already understands through metaphor or using a model to demonstrate a topic should further the audience's cognitive engagement (Johnston & Taylor, 2018).

Novelty

Another critical aspect of engagement is the novelty of the information presented. Knowledge transfer and building excitement are two highly prioritized science communication objectives (J. C. Besley, Dudo, & Yuan, 2018). Even though simple knowledge transfer and deficit model communication is known to be ineffective, Brossard and Lewenstein demonstrate how sharing new information surrounds every model of science communication as a central force including those focused on engagement (2010). Knowledge and excitement are also important in traditional linear models of science, where research leads to new findings that apply to industry and new technologies for public use (Pielke, 2007).

Interaction

The last potential factor represents a major portion of engagement's behavioral component (Johnston & Taylor, 2018). Participation, collaboration, action, and involvement contribute to the idea of interaction important for higher quality engagement. The bulk of interaction engagement examines online or digital channels from the user engagement model (Jeeyun Oh et al., 2018), a public relations scale for blog engagement (Hopp & Gallicano, 2016), and how Twitter serves as a participation space for science topics (Young et al., 2018). The current study does not differentiate between digital and in-person interaction. The actions taken for digital interaction, like clicks or other interface use, are often inconsequential compared to in-person interaction with a science communicator. However, there are far fewer opportunities for in-person interaction, and most studies focus on science festivals due to the difficulty of researching other modes of in-person interaction (Sardo & Grand, 2016). The current conceptualization stays indifferent to the mode or place of communication and focuses on an overall interaction measure regardless of place.

Together these seven hypothesized factors make up the major structure of SCER. An initial item pool generated 41 items with at least three items per theoretical dimension (Table 1). Since the theories that guide the hypothesized factors either have reliable measurement tools already validated, most of the items have been adapted to the context of science communication (Organization-Public Dialogic Communication Scale and the Muenster Epistemic and Trustworthiness Index). The remaining items have derived from ideas in science communication objectives and literature and literature from communication engagement regarding interaction. The following steps in scale development involve measuring and assessing the validity and reliability of the scale. The complete development steps are conducted in the next chapter, followed by factor analyses to address the potential scale's validity and reliability.

SCER Dimension	Item Wording (*This scientist…)*	OPDC	SCO	METI	BE
Empathy	is empathic in understanding publics' feelings	X			
	tries to understand problems from publics' perspectives	X			
	can estimate how publics might feel now	X			
Respect	retains positive regards despite different opinions	X	X	X	
	recognizes the unique value of publics' opinions	X	X	X	
	is altruistic in accommodating publics feedback	X	X	X	
Grounding	tries to establish that publics correctly understood	X	X		
	invites publics to communicate	X	X		
	shares common ground of communication with publics	X	X		
Collaboration	communicates together for mutual betterment	X	X		X
	can deal with publics diverse perspectives effectively	X	X		X
	accepts publics opinions as worthy of consideration	X	X		X
Accessibility	shares open access of information to all publics	X	X		
	allows publics to the opportunities to share their opinions	X	X		
	is easy to talk to	X	X		
Genuineness	is honest in communicating with publics	X	X		
	is straightforward in communicating with publics	X	X		
	genuinely commits to the conversation with publics	X	X		
Transparency	is transparent in sharing their intent of communication	X	X		
	is clear to understand when it communicates with publics	X	X		
	is not deceptive in interpreting publics' opinion	X	X		
Expertise	is competent in their field		X	X	
	is well educated		X	X	
	seems insincere about their intentions		X	X	
	demonstrates fairness towards others		X	X	
	is ethical about their research		X	X	
	is not considerate of others		X	X	
Altruism	understands how people think about the work that scientist do		X	X	
	showed an interest in learning from my community		X	X	
	made me think about future decisions that could be informed by science.		X	X	
Framing	framed things so that they made more sense for me		X		
	compared the topic with something else I already understood		X		
	did not present information that felt close to home		X		
	demonstrated the topic to me		X		
Novelty	presented new information to me		X		
	was excited to share their findings with me		X		
	downplayed their discoveries		X		
Interaction	spent a lot of their time with me				X
	created an opportunity for me to interact with the topic				X
	discouraged interaction				X
	did not give the opportunity for follow up questions				X

Table 1: Science Communication Engagement Response scale item pool with association subscales. Organization Public Dialogic Communication (OPDC), Science Communication Objectives (SCO), Muenster Epistemic Trustworthiness Index (METI), Behavioral Engagement (BE).

Chapter IV: Methods

Scale Development

Scale development through classical test theory (CTT) for the latent variable for SCER in this dissertation. A scale consists of effect indicators whose cause is an underlying construct, the latent variable. The justification and logical linkages between existing theories described in the literature review and theoretical foundation represent what Chaffee termed a “meaning analysis” (1991). These structures represent factors that make up the underlying latent variable. The items are then collected and combined into a composite score that reveals the latent variable (DeVellis, 2016). CTT is one approach to measuring latent variables that assume one underlying variable (in this case, science communication engagement) is the common cause for answers on the scale. Observed scores are the result of the variable’s true score plus error. True scores are never fully known but are inferred from observed scores from a survey or interview. The observed score and any error present in the measurement make up the latent variable's relationship to the survey items. Other approaches offer different ways to rank items or interpret error, but CTT provides the best option for the proposed scale.

CTT is based on parallel tests where each item represents a test of the latent variable. There are three measurement assumptions included in CTT. The first assumption is that error associated with individual items is randomly varied. Error with individual items has a mean of zero when taken across a large number of people. Thus, item means are unaffected by error when using a large enough sample. Another assumption is that one item’s error is not correlated to other item errors. The only route that links items is through the latent variable. A third assumption states that error terms and true scores of the latent variable are not correlated. Instead, error terms correlate with observed scores, and observed scores derive from the latent variable's true scores. The first two assumptions are consistent with other statistical methods. The third defines an error for each item as the left-over value after considering a set of items and their latent variable.

Additionally, there are two assumptions involved in the parallel tests model used in the current analysis. The first states how each item's influence from the latent variable is assumed to be the same for all items. The second assumption is each item has the same amount of error as any other item. This means that the influence of factors other than the latent variable is equal for all items. These assumptions describe how correlations between each item and the true score are identical and define how each item may or may not be valuable to the scale. These last two assumptions are essential for calculating scale reliability.

RELIABILITY

If a car doesn't start immediately or has constant mechanical issues, some would say that car isn't a reliable means of transportation. The car doesn't perform in consistent, predictable ways. The same is true for a scale. Scale reliability depends on scores reflecting some actual state of a variable, and it should perform consistently regardless of when it's administered. The strict definition for measurement reliability is the proportion of variance attributable to the latent variable's true score (DeVellis, 2016). The most common way to assess the reliability of a set of measures is Cronbach's coefficient α. This is a crucial estimate of the internal consistency of a collection of items. The estimate is used in nearly all multi-item measures for social science research (Cronbach & Meehl, 1955). The same process assesses a scale's reliability. Variance for any set of items reflects one of two things: actual variation across individuals in the intended variable measures or measurement error. Ideally, α for a collection of items would be 1.00. This would indicate that there was no error in the transfer of information between the sample participants, the survey instrument, and the conceptualization of the latent variable. However, there will always be error in measurement because there will always be noise, or error, surrounding the signal, the variance.

Cronbach's coefficient α does an adequate job at assessing a set of items' internal consistency reliability, but it is not without its flaws. Cronbach's α is a conservative measure and represents lower bounds of reliability (DeVellis, 2016). Another criticism is that it was initially created with continuous data, and α determined from ordinal data can be inaccurate. To remedy this, Gaderman et al. (2012) recommend an alternative measure they call ordinal α. This α estimate does not assume interval scaling and replaces Pearson correlations with polychoric correlations. These correlations are best used in data that is ordinal with multipoint response options present in the current study. Additionally, scholars also recommend the use of confidence intervals and bootstrapping. Confidence intervals will help the current study establish faith in the point estimate from ordinal α, and bootstrapping simulates data based on the sample provided with α values for each sample resulting in a distribution of α scores, a basis for determining confidence intervals.

VALIDITY

If a scale is reliable, it has a high probability of consistently measuring the same thing for different samples of the population with limited error. However, the scale developer should make sure that the scale is actually measuring the variable of interest. A common analogy used to differentiate the two terms is imagining three dartboards. One board has a cluster of darts on it, but the darts are off-center from the bullseye. This board is the same as a scale with high reliability but low validity. The second board has one or two darts close to the center but just outside the first circle. This board is said to have high validity but low reliability. Finally, the third dartboard has all darts clustered together and close to the center. This dartboard has high validity and high reliability. Validity refers to whether the underlying variable is the cause of item variation represented in a measure of α. Unlike reliability, scale construction determines the validity, not measurements alone. Validity is split into subcategories that represent different forms. Some have said there are six forms of validity to evaluate and attend to during scale development (Messick, 1995). However, a more commonly adopted framework contains only three categories to maximize overall scale validity.

The first type of validity is content validity. Content validity is the extent to which a specific set of items reflects a content domain. A content domain contains every possible item that could measure the latent variable. Maximizing content validity involves a group of equally appropriate items compared to the universe of possible items (DeVellis, 2016). It is a direct reflection of the relationship between the conceptual definition and the latent variable. Researchers talk with and interview subject matter experts around the latent variable to maximize content validity (Carpenter, 2018).

Interviewing experts, research scholars, and practitioners can gain insight for tailoring items in the initial list. In the current study, 13 in-depth interviews were done to assess content validity. A full description of the process and results is discussed below.

The sconed type of validity in scale development is criterion-related validity. Sometimes called predictive validity, criterion-related validity is a scale's empirical association to some gold standard related to its purpose. This is more of a practical issue than a methodological one. Scales with good criterion-related validity tend to be useful for researchers and practitioners using the tool to improve some aspect of their job. The current paper does not address criterion-related validity, although future research opportunities will be explored in the subsequent discussion. This type of validity is also synonymous with concurrent and postdictive validity. The difference is in the temporal nature of the intended outcome.

Finally, newly developed scales can maximize construct validity by comparing itself to known constructs and measurement tools. These scales address the relationship between the new scale and similar or different variables. This is called construct validity. Established measures conceptually similar to the newly created scale should correlate, where established measures that are conceptually different should not correlate. This ensures that correlations between predicted variables provide evidence of how well the new scale behaves, as does the latent variable it is supposed to measure. For a scale concerned with science communication engagement, the current study used two variables that should have high correlation with the latent variable, two variables that can assess both on a continuum, and one variable that should demonstrate low correlation based on theoretical understanding.

SUBJECT-MATTER-EXPERT INTERVIEWS

The list in Table 1 is the first major step in scale development, but finalizing this list includes gathering feedback from other scholars and professionals in science communication and engagement (Carpenter, 2018; DeVellis, 2016). Before any data analysis or survey distribution began, qualitative in-depth interviews were conducted with subject matter experts in various science communication and engagement fields. Expert interviews about the latent variable and theoretical linkages are useful to confirm or invalidate the conceptual definition, evaluating clarity of dimensions, and can provide perspectives on the latent variable scale developers may have overlooked (DeVellis, 2016). A total of 13 interviews were conducted during the Fall of 2020, with interviewees in three categories representing critical science communication practice and scholarship areas. One group contained eight science communication researchers from different universities, including Michigan State University, University of Wisconsin – Madison, University of Utah, Texas Tech University, University of Iowa, Northern Illinois University, Technion – Israel Institute of Technology, and Oregon State University. These researchers were picked through existing network ties with the author. Another group consisted of science communication trainers and practitioners. These four experts were also gathered through network ties with the author and represent prominent training and outreach organizations in science communication, including the Alda-Kavli Learning Center at Stony Brook University, the American Association for the Advancement of Science, COMPASS, and Portal to the Public. The last group was made up of communication engagement researchers. Although only one completed interview was possible for this group, the information was invaluable to the set of items created. All participants were contacted via email for 10–15-minute interviews through video conferencing software.

All interviews were conducted by the author, and transcription was done automatically through the web application. Notes were taken during each interview for quotes of interest and reminders to the author to double-check transcriptions. A list of questions acted as a guide for each interview, but a more fluid approach was taken if interviewees presented an answer that necessitated follow-up questions or more elaboration. The set of questions included asking interviewees about their interpretation of science communication engagement broadly. If they mentioned a dimension described above in the meaning analysis, follow-up questions were asked for more clarification. Finally, questions about the importance of one of engagement dimensions outlined by Johnston and Taylor (behavioral, cognitive, or affective engagement) (2018). In addition to these questions, the interview process evolved based on new information emerging from each interview. This method can have a more significant impact on interview results because topics and questions that may not have been thought of during the design phase can emerge (Babbie, 2015).

The goal of each interview was to gather information on participants' thoughts about the latent variable concerning the scale dimensions explicated in the meaning analysis. Interviews can help maximize the content validity of the final scale and are common in scale development procedures (Batchelder et al., 2017; Carpenter, 2018; Hartman et al., 2017; Hendriks et al., 2015; King, Jensen, Davis, & Carcioppolo, 2014; Yang et al., 2015). To achieve this, a hybrid approach of computational and manual text analysis was performed. Since the purpose of the interviews is to aid in the scale development process and not a separate study with its research questions and hypotheses, this hybrid approach allowed the researcher to comb through transcripts and efficiently analyze important discussion topics. Quotes found from the computational analysis were collected for analysis and final discussion. Both methodologies have their place, and both are used for similar data sets where large amounts of text need to be scrutinized for underlying themes. The benefit of non-computational methods is that a researcher can do a deep dive into their data and better understand emergent themes. These themes are iteratively discovered within the data through hours of reading, labeling, and making connections within and between documents. This method is widely used in studies where it is the primary focus or when multiple coders and researchers are involved. Computational text analysis, on the other hand, is a much faster process.

Discovering themes (or topics) in a dataset between and within documents is still the primary goal. The difference comes through the computational topic models used to achieve thematic categories. These models take a collection of documents, or a corpus, and separates the words within each document to look for topics within those documents from recurring word patterns (Maier, et al., 2018). One model often used is the Structural Topic Model or STM (Pituch & Stevens, 2015). An STM is the generative model of word counts where document-topic and topic-word data is gathered within the corpus. An STM topic is a mixture of words that each have a probability of belonging to a set number of topics, and a document is a mixture of topics. In this case, a single document of the recorded interview from one participant is composed of multiple topics.

Once all interviews were completed, the automated transcripts were downloaded and labeled for each participant. The transcripts were put into the R environment to start the cleaning process. R is a coding language made for data analysis. It has been rising in popularity due to the open-source and accessible platform for academics and data scientists to clean, visualize, and model data (Fox & Leanage, 2016). The R language was used through the R Studio graphical user interface, and subsequent code will be available in dissertation appendices and supplemental information. In text analysis, any unwanted symbols numbers and auxiliary text needs to be excluded from the data so the STM will run correctly. All lines of the transcript where the researcher was speaking, timestamps where only numbers were present, and blank lines were removed from the data set. The final dataset contained 1,695 observations and three variables that included the line number from the original transcript, the text from the participants, and the participant's name. This dataset would allow the researcher to analyze topics and reference the line of text where topics were most prevalent and who said those lines.

Computational Text Analysis

The STM was performed in the stm package through R, and then results were analyzed through a web application made for R packages called Shiny Apps. A Shiny App uses R code related to a dataset to build interactive visualizations. The tool allows users to skip the step of manually coding data visualization (Welbers, Van Atteveldt, & Benoit, 2017). Data were conformed into a document term matrix that is needed for the STM to work. This matrix separates all words in the corpus and records how many times those words appear in each document. From there, model parameters were created for a three-topic model. The low number of topics were chosen based on the content of the interview.

During each interview, topics regarding the latent variable would be brought up over multiple interviews with different subjects. Most discussions began to revolve around similar ideas toward the last few scheduled interviews. This saturation of interview content concluded that there would be only slight variation between topics in the computational analysis. The three-topic model was put into the Shiny web application stminsights and the words with the highest frequency weighted by how exclusive they are to the topic. The first topic included the words important, evaluate, create, belief, and listen. The documents where these were most prevalent included two participants in the practitioners' group that where interviews had a 43% and 42% probability of containing those topic words. The other document included one science communication researcher with most of their work done on the communication training that had a 40% probability of containing those topic words. The second topic included the words media, videos, context, content, message, and expertise. The documents where these words were most prevalent included interviews from two science communication researchers with 70% probability coming from one and 43% coming from the other. Another interview came from the expert on communication engagement, where 64% of their interview contained words from topic 2. The last topic in the model included the words public, dialogue, process, motivation, outcome, and cognitive. Again, this topic had high occurrences from two of the three groups interviewed. Two science communication researchers had 62% and 48% probability of their interviews containing these words, and a science communication practitioner had a 36% probability. The topic proportions over each document were 38.2% for topic 2, 33.2% for topic 1, and 28.5% for topic 3. All topics were distributed almost equally across all documents reinforcing the initial high saturation of content for each interview.

To transition to a more qualitative analysis on the three topics, the top three interviews for each topic were evaluated for the lines of text that recorded high theta values for their topic. Theta is the proportion of a document (lines within an interview) allocated to a topic (Roberts, Stewart, Dustin, & Harvard, 2014). Those lines were then recorded and used as waypoints to search through each corresponding interview—these markers made for an easier search for influential discussion points within the corpus.

Interview Findings and Topic Interpretation

Overall, discussions during the interviews were similar across participants and participant groups. Science communication researchers, content area practitioners, and the communication engagement expert discussed similar ideas about public engagement with science. The topics generated by the STM also had similarities to one another and between all interviews. Topic 1 can be explained as discussion relevant to the evaluative process of science communication engagement. Many of the participants talked about the importance of a scale that could measure engagement within science. One practitioner discussed how evaluating the impact of science communication cannot be made up of "loosey-goosey" goals that aren't said aloud. Instead, they ask, "Or, are we going to be honest with ourselves around what it is we're actually trying to do and evaluate our impact on that." This idea of engagement as a better evaluation tool for scientists' communication goals was also echoed by a science communication researcher who had a high probability of discussing this topic according to the STM. A lot of research described in earlier chapters use interaction as a proxy measurement for engagement, but interaction is just one piece of the bigger picture. They reinforce this with questions to scientists like, “why do you want to change? Why do you want to affect somebody’s emotions right there?” This participant went on to talk about how cognitive processes will eventually lead to other engagement dimensions and attributes like behavioral engagement and affective engagement (Johnston & Taylor, 2018). This quote sums up how engagement is more than just interaction:

> So, if I engage in an activity, we can use that as “I take part in an activity.” But, I’m going to argue that we have this separate term, we need to take that seriously and it should be, ‘I didn’t just take part in an activity, but I engaged in the activity. I actively, cognitively engaged in the activity. I was motivated to participate.

Activity and interaction are not equal to engagement, which is one reason why a scale needs to be developed in the first place. This is also why the interaction dimension is just one of the many include in science communication engagement. Another participant echoed this idea and argued how most science communication engagement is “making adjusted approaches to informal education” that include emotional appeals to the audience to get them to invest in the effort to learn. However, they go on to say how it’s more than knowledge transfer and building connection to help future beliefs:

> Other times, public engagement refers to getting non-scientists actually involved in the process of science, so that they can have a say in policy governance and actually dictate the direction that science goes.

Getting others excited about science, showing empathy with your audience, demonstrating how science can benefit society are some of the core ideas behind the dimensions of science communication engagement. If a multi-measure variable can include these ideas, we can be one step closer to scientists creating high-quality public engagement.

The second topic revolved around ideas of science communication and engagement in context. This idea that science communication like all strategic communication is contextual Different objectives and tactics depend on the audience, the subject matter, and the media channel where communication takes place. Several participants in topic one talked about goals in science communication. The same is echoed here in topic 2. One of the science communication researchers with a high probability of discussing terms related to topic 2 mentioned that not having a goal can be difficult for scientists. They talk through different contexts where goals could differ depending on the content like when scientists communicate their research findings they might want to stay in their domain of expertise. However, science communicators who are more concerned with advocacy shouldn't feel locked to a specific content domain. Scientists' social media interaction also made up many of the discussions throughout the interviews. The subject matter expert on communication engagement discussed ideas mentioned earlier in topic 1, but they also talked through how it is a lower tier of engagement quality where exchange in social capital would demonstrate higher tiers. They talked about how there's "always consequence from communication, but the consequence needs to be significant for both parties." This idea is represented in grounding, collaboration, and accessibility dimensions in the explication of science communication engagement above.

> Engagement creates that relational capital that creates that ongoing value that comes from having that exchange and interaction and the resources and effort that go into it.

These separate tiers or spectrum of engagement quality were also discussed in another participant interview within topic 2. This science communication scholar talked about a wide range of public engagement activities from putting out a medicinal or technological product to the public at the one end and closing a lab due to ethics issues at the other end. This science communication researcher talked through similar public engagement ideas, but differed from the majority of researchers in their belief that strategic communication does not provide helpful guidance for how we conceptualize science communication. However, their outlook on science engagement was the outlier among the experts interviewed.

The final topic from the STM revolved around the idea of dialogue. This finding aligns well with several dimensions theorized in the meaning analysis. One science communication researcher with a high probability to talk about this topic talked through the process of engagement in terms of dialogue, “I think everything starts with behavior. It could be like, you know, I wanted to talk to the scientists online, talk to them in person, or I’m going to change my behavior based on what I see or hear.” For this researcher, dialogue can be a starting point or the catalyst for engagement. Others who research this idea are split about whether dialogue is a part of engagement or if engagement is a part of dialogue (Taylor & Kent, 2014). The distinction between the two frameworks is what someone sees as the ideal outcome. Many public relations scholars look at dialogue as the outcome and engagement as the breadcrumbs to get an audience there. However, for scientists and science communicators, the framework is reversed. Public engagement is achieved through dialogic, two-way communication. I think engagement is the ultimate goal and dialogue is one way to get there. In my view dialogue makes for a smooth transfer from simple interaction to high-quality engagement. Part of the idea of good dialogue includes being a good listener. As explained in the meaning analysis, dialogue is not just about you talking to them (I-It). It’s a mutual exchange of open communication from both parties (I-Thou). One of the practitioners involved in science communication training courses talked through this idea:

> Even if that listening involves non-verbal listening because I think sometimes you get that from people asking, ‘How can I possibly listen to an audience of 400 people?’ It’s harder for sure than me and you having a conversation here, but there are ways to bring that intention into your communication. Maybe you’re utilizing some polling that you can do if you’re online. There is always ways to integrate listening as core elements of you communication, and to me, a fully engaged communicator is always focused on that.

To them, full engagement necessitates active listening with your audience regardless of size. This idea is also central to the dimensions of empathy and grounding from previous research on dialogic communication and science communication objectives mentioned earlier in the dissertation. Another focal point of dialogue is interactions that contribute to society and promote collaboration (Taylor & Kent, 2014). When talking through good examples of science communicators, one researcher with a high probability to use words associated with topic three discussed how some well-known scientists are doing a good job, and others might be too divisive without reason:

> I would make the distinction between opinion leaders who are within this like science atheism world, and science communicators who are actually trying to not just trying to explain science, but trying to advocate on whichever issues. And in some ways, Leonardo DiCaprio is an even better science communicator than someone like Neil deGrasse Tyson because you have someone who’s using his popularity in a way to leverage people’s concerns about an issue without trolling groups and creating divisions.

Their commentary on the well-known scientist communicator Neil deGrasse Tyson highlights how good intentions don't guarantee effective communication (Little, 2019). To the extent that a scientist communicator seeks to maximize the positive impacts of their engagement efforts, they need to understand how their audiences interpret their communication behaviors. Without this sort of assessment, how can they accurately judge the ways in which their communication intentions (i.e., their goals and objectives) are being met or missed?

These interviews provided valuable feedback on the focal concept of science communication engagement. The majority of participants confirmed what was already theorized in the above meaning analysis. Overall, this exercise helps to substantiate the idea that an attempt to evaluate the efficacy of science communication engagement efforts should take into account the extent to which the effort (1) conveys clear objectives, (2) boosts trust, and (3) facilitates dialogue and interaction among experts and their audiences. And, since engagement is determined by the audience and not the speaker, the best way to measure this is with a response scale from a communicator's intended audience. The findings discussed here maximize the scale's content validity and established the importance of a measurement tool like this. One of the science communication practitioners said it best:

> There's a lot of reasons why a scale might not work. But what I don't want to lose sight of is the fact that you're addressing something which is super important. We're trying to be better as an organization about the, you know, survey evaluation we do on the scientists we train. But as they say the Holy Grail is to actually look at who they're engaging with and see if the training made an impact. That would be amazing. That would be really cool.

SURVEY

Evidence from the interviews reinforced the existing item list (Table 1), and no new items or theoretical dimensions emerged to warrant additional items. A research company was utilized to distribute the scale items, validation items, and demographic measures. The target sample was set to 410 to achieve a 5:1 ratio between participants and the number of items (Carpenter, 2018). The total sample was randomly split into two equal subsamples. The first sub-sample was used for exploratory factor analysis, and the second sub-sample was used for confirmatory factor analysis. The next section describes the survey procedures, measures, and sample's descriptive statistics.

Procedures

Respondents self-selected into the survey distributed through Qualtrics, a widely used online survey platform. Participation in the survey and all subsequent information was kept confidential, and respondents were told they could opt-out at any time. The survey was estimated to take approximately 10 minutes to complete. Additionally, information to contact the author and the principal investigator named on the International Review Board application, Anthony Dudo, Ph.D., were available. The next set of questions were designed to screen out participants who did not meet specific study criteria.

Initial screening items were done by the research company to meet quotas for a sample distribution that reflected information from the 2020 census. A gender question that asked respondents to choose "male," "female," "Other gender not mentioned," or "Prefer not to say" was used to gather a sample of 45% male, 45% female, and 10% from the remaining two answer choices. These answer choices are not an accurate representation of current measurement tools used for gender (Westbrook & Saperstein, 2015). This screener question allowed for estimated groups from the most recent U.S. Census and possible respondents who don't conform to traditional gender groups. Similarly, a question about racial groups was used as a broad category for initial screening that included answer choices for "White," "Hispanic or Latino," "Black or African American," "American Indian or Alaska Native," "Asian," "Native Hawaiian or Pacific Islander," and "Other." A more detailed race and ethnicity survey item was used for item analysis after scale items were collected. This question asked respondents to identify their race as best as possible and utilized the most recent census percentages of the U.S. population of these broad categories. The quotas were set to 45% White, 25% Hispanic/Latino, 15% Black, 10% Asian, and 5% for all other answer choices.

Additional screening questions were used to gather respondents with at least some interest in science and technology news or information. One set of questions asked, "How interested are you in news about each of the following topics" that included government and politics, local community, sports, business and finance, science, and entertainment. Answer choices were on a scale from 1 (Extremely interested) to 5 (Not interested at all). The only item used for screening was the answer choice of "Not interested at all" for science news and information. If any other answer choice for science, 1-4, was chosen, they went on to the next question. The last question asked respondents if they were interested (Yes or No) in the following science-related topics: health and medicine, technology, energy and environment, food and nutrition, space and astronomy, the evolution of humans and animals, the mind and brain, none of these or other. If respondents chose “Yes” for none of the above topics, they were removed from the survey and did not receive any further questions.

After initial screening questions, participants went through the full set of convergent and discriminant validity items followed by an attention check that told participants to pick a specific color from a list. After that a short open response question about past experience with a science communicator followed by the scale items and demographic questions. The final sample yielded 431 completed responses. The initial sample was imported into a spreadsheet and then cleaned for respondents who finished the survey in less than half the median time of 210 seconds. The main scale items were then used to calculate a standard deviation measure to filter out any straight lining that may have taken place. Participants who chose the same answer choice for every scale item (i.e., all 3’s or all 5’s) were excluded from the final sample. If the standard deviation for participants was calculated as 0.00 for the scale items, no variation in item response was recorded for that participant which indicated straight lining responses. Their surveys were excluded from the final analysis. The final sample yielded n = 404 responses. This final sample size is sufficiently large enough for two sub-samples to meet the recommended 5:1 participant to scale item ratio for subsequent exploratory and confirmatory factor analysis (Carpenter, 2018; DeVellis, 2016).

Measures

Survey items after the screener questions fell into one of three categories. The first set of items was a collection of previously identified multi-item scales and variables integral for establishing construct validity. These eight variables were all arranged on a five-point scale except for a measure for science literacy. The next set of items included the items for scale creation (Table 1). This survey section had one open-ended question, a question to place respondents in either a category for positive or negative interactions with scientists/science communicators and the scale items on a five-point scale. The final set of questions collected demographic information from respondents. All items were coded after survey completion so that higher numbers indicated higher levels of the variable being measured.

Science News and Information Interest. The first set of measures was an adapted scale to gauge why people might follow science news and information (Pew, 2017). The question stem stated that “People follow news and entertainment about science for different reasons. For each of the following reasons, please indicate your level of agreement.” The stem was followed by seven reasons participants responded to on a five-point scale ranging from strongly disagree to strongly disagree. Reasons included “talking about what’s happening with others,” “it is related to things I need to know for my job,” “it helps me make decisions,” “social or civic obligation to stay informed,” “curious about science,” “it is related to my hobbies or interests outside of work,” and “it is related to my children’s activities or interests.” These items yielded an $\alpha = 0.84$ ($M = 3.75$, $SD = 0.72$) that demonstrated internal consistency as a composite variable, but the final construct validation left items separated.

Science Literacy

Science literacy questions were asked to evaluate participants' knowledge about concepts central to learning about the world around us (National Science Board, 2018).

Historically, science literacy is only a somewhat useful science engagement measure due to its reliance on knowledge objectives and nothing regarding attitude (J. Besley & Dudo, 2017; Stylinski et al., 2018), but the current study uses it as a construct validation item. Six items asked respondents to answer statements with either “False,” “True,” or “Don’t Know.” Respondents who answered incorrectly or “Don’t Know” were coded as 0, and correct answers were coded as 1. Statements in the measure included “It takes one year for the Earth to go around to Sun,” “All radioactivity is man-made,” “Lasers work by focusing sound waves,” “Electrons are smaller than atoms,” “It is the father’s gene that decides whether the baby is a boy or a girl,” and “antibiotics kill viruses as well as bacteria.” The majority of respondents answered at least three out of the six items correctly (M = 3.17, SD = 1.60). The composite score for science literacy was used in the final model for construct validity.

Science Career Interest

Items were included to measure respondents' interest in scientific occupations. These items were adapted from the Oregon Vocational Interest Scale (ORVIS) (Pozzebon, Visser, Ashton, Lee, & Goldberg, 2010). Using a five-point scale from “Like a great deal” to “Dislike a great deal,” these items gather information for how much someone would like scientific careers and activities. Nine items included with the stem “How much would you like or dislike the following given your current career trajectory or if you could start a new career?” asked about “Being a chemist,” “Design a lab experiment,” “Mathematician,” “Explaining science to others,” “Being a physicist,” “Medical research,” and “Scientific reporter.” These items yielded an $\alpha = 0.88$ (M = 3.42, SD = 0.84) that demonstrated internal consistency as a composite variable, but the final construct validation left items separated.

Promise of Science

One item measured respondent's views on science as a benefit or not to society (National Science Board, 2018). The question asked respondents to weigh the benefits compared to the harmful results of science on average. Answer choices were selected from a five-point scale from "Benefits strongly outweigh harmful results" and "Harmful results strongly outweigh benefits." The majority of responses reflected a beneficial feeling about the promise of science for society (M = 3.96, SD = 1.06).

Science Funding

One question was asked about scientific funding from the federal government "even if it brings no immediate benefits." This item was adapted from the National Science Board Science and Engineering Indicators and is commonly used to indicate positive belief in science (National Science Board, 2018). Answer choices were placed on a five-point scale ranging from "Strongly agree" to "Strongly disagree." The majority of respondents recorded answers that strongly agreed with funding for science from the government (M = 4.16, SD = 0.85).

Cultural Worldview

To measure how much respondents believe in scientific consensus across multiple science domains, two subscales were adapted from the Cultural Cognition Worldview Subscales (Kahan, Braman, Gastil, Slovic, & Mertz, 2007; Kahan, Jenkins-Smith, &

Braman, 2011). The first set of questions measured respondents on the Communitarian-Individualistic subscale. This measure reflects how individuals value the group in a person's social and political life. Higher values on this set of questions indicate a more communitarian worldview and lower items indicate a more individualistic worldview. All items within both subscales stemmed from the statement, "The following questions are related to how you see the world around you. To the best of your ability, please answer how much you agree or disagree." Items included a five-point response from "Strongly disagree" to "Strongly agree" for statements like "Sometimes the government needs to make laws that keep people from hurting themselves," "The government should do more to advance society's goals, even if that means limiting the freedom and choices of individuals," and "Government should put limits on the choices individuals can make so they don't get in the way of what's good for society." Three additional items were negatively worded that included "The government interferes far too much in our everyday lives," "It's not the government's business to try to protect people from themselves," and "The government should stop telling people how to live their lives." These last three items were reverse coded to indicate higher levels of communitarian beliefs for higher values. Another set of items included measures from the Egalitarian-Hierarchical subscale is used on beliefs related to some people or groups are better than others. Respondents were asked to record answers using the same question stem and five-point scale to statements like "Our society would be better off if the distribution of wealth was more equal," "We need to dramatically reduce inequalities between the rich and the poor, whites and people of color, and men and women," and "Discrimination against minorities is still a very serious problem in our society." As with the previous subscale, three items were negatively worded and reversed upon data analysis. These questions included, “We have gone too far in pushing equal rights in this country,” “It seems like blacks, women, homosexuals and other groups don’t want equal rights, they want special rights just for them,” and “Society as a whole has become too soft and feminine.” These items yielded an $\alpha = 0.52$ ($M = 2.95$, $SD = 0.73$) for the Communitarian-Individualistic scale and $\alpha = 0.75$ ($M = 3.35$, $SD = 0.93$) for the Egalitarian-Hierarchical subscale that demonstrated internal consistency as a composite variable. Variable items were left separate for final validation models.

Conspiracist Ideation

Finally, one last variable was used to exemplify discriminant validity with the latent variable. This set of items assesses beliefs about the existence of conspiracies that have shown a negative correlation with positive science beliefs and interests (Lewandowsky, Gignac, & Oberauer, 2013; Lobato, Mendoza, Sims, & Chin, 2014). The stem included the statement, “There is often debate about whether or not the public is told the whole truth about various important issues. This brief survey is designed to assess your beliefs about some of these subjects.” Answers were recorded on a five-point scale from “Definitely not true” to “Definitely true.” Statements following the stem included common beliefs among people who have a high tendency to believe in conspiracy theories like “The government permits or perpetrates acts of terrorism on its own soil, disguising its involvement,” “Certain significant events have been the result of the activity of a small group who secretly manipulate world events,” “Evidence of alien contact is being concealed from the public,” “Experiments involving new drugs or technologies are routinely carried out on the public without their knowledge or consent," and "New and advanced technology which would harm current industry is being suppressed." These items yielded an $\alpha = 0.75$ ($M = 3.26$, $SD = 0.93$) that demonstrated internal consistency as a composite variable. Variable items were left separate for final validation models.

SCER Scale Items

The final set of items included two items that supported the scale items and the scale items for subsequent factor analysis. The first question before the scale items asked respondents to "Describe a time where you interacted with a scientist about a science topic." The interactions could have been visiting a museum and listening to a scientist's talk, watching a video about science, listening to a radio show or podcast about science, or reading something on the internet or a book about science and technology. Respondents were encouraged to elaborate in an open-ended response. This technique was adapted from Elaboration Likelihood Theory which attempts to measure how much cognitive effort a person uses following an experimental condition (Petty & Cacioppo, 1986). These measures are often used as a proxy for engagement. However, this study used this item to bring past experiences with scientists or science communicators to the respondents' top of mind. After the open-ended question, the survey then asked respondents to rate the scientist from 1 to 6 with no midpoint of how positive or negative they perceived the experience with "Extremely positive" on one end and "Extremely negative" on the other. This item was included to allow respondents to answer the scale items based on their experience rather than ideal or imagined public engagement behavior. This way, the study ensured accurate measures of response to science communication engagement regardless of quality. Only 30 respondents (7.43%) used the memory of a negative experience with a scientist (M = 4.49, SD = 1.09).

The following 41 items contained the scale creation items with ten items reverse coded based on wording to reflect the potential factor's higher measures (Table 1). Due to the rating question mentioned above, respondents who answered the questions based on a negative experience were then reverse coded once more. All responses pointed toward ideas of greater values of the latent variable. The overwhelming majority of items were found to be non-normal in their distribution, with all scale and validation items containing p values less than 0.05 for the Shapiro-Wilkes test of normality. This non-normal distribution is also apparent in the items' tendency to be positively skewed.

Missing Data

Data cleaning and subsequent analyses were done in R, just as the computational text analysis. After the final dataset was established from the research company, the raw data were imported into R and examined for missing items on key variables. These key variables included all scale items and any items that were a part of construct validity scales. There were missing data issues on variables used for construct validation measures, but due to in-survey prompts that encouraged (but did not enforce) responses to scale items, there were no missing responses on any of the 41 items used for scale creation. A hot-deck imputation was used to correct missingness in all non-demographic variables. Hot-deck imputation uses similar respondents in a sample to impute missing values of a set of variables. The responses from similar participants, either in demographics or answer choices from other variables of interest, are used as a "deck" to impute missing values (Enders, 2010). Originally developed for use at the Census Bureau (Scheuren, 2005), hot-deck imputation is a popular method to address missingness in survey literature but has seen less use in behavioral and social science research. This method is an efficient alternative to other techniques common in social science research, such as listwise or pairwise deletion (Myers, 2011). The full dataset of returned 333 missing observations across all scale and validation items. The majority of missing items came from questions about why people follow science news and information (87%). Missing responses were not imputed for demographic variables to keep the as true to the sample as possible.

Sample

The sample makeup was sufficiently similar to past census data due to parameters set up in the survey gathering stage. Out of the total sample (n = 404), 31.7% said they were of Hispanic origin. The majority of respondents recorded their race as White (57.4%), followed by Black (19.8%), then Asian (12.1%), with the remaining sample spread across Native American or Native Alaskan (6.9%), Pacific Islander or Native Hawaiian (1.2%), Middle Eastern (0.5%), and a race not listed (2.5%) The average age was 67 (SD = 24.82, n = 372) with a range from 19 to 98 years old. Respondents were fairly split across gender with Male (51.0%) recorded about as much as Female (48.5%), followed by only two respondents (0.5%) who reported "Other gender not mentioned."
Political identification and political ideology were recorded for each respondent. When asked to identify what political party they think of themselves as, most respondents

recorded themselves as Democrat (49.3%) followed by Independent (24.5%), Republican (19.1%), no preference (6.0%), and Other (1.2%). When asked about political ideology on a six-point scale ranging from "Extremely Conservative" to "Extremely Liberal" 63.9% of respondents recorded themselves ranging from somewhat liberal to extremely liberal (M = 3.94, SD = 1.39, n = 404). The education level of the sample was fairly dispersed. On a scale from 1 to 8 ranging from "Less than a high school degree" to a "Professional degree (JD, MD)" most respondents indicated they finished at least an associate degree if not more (M = 4.00, 1.55, n = 404). The most chosen response was a finished bachelor's degree (37.4%), followed by some college (21.3%). The final demographic question presented a picture of yearly income for survey respondents. On a scale from 1 to 6 ranging from "Less than $24.999" to "$150,000 or more", the average respondent made somewhere between $50,000 and $74,999 (M = 2.94, SD = 1.51, n = 402) in their income for the last year before taxes. The most chosen response for income was $24,999 to $49,999 (28.4%).

Chapter V: Results

EXPLORATORY FACTOR ANALYSIS

An Exploratory Factor Analysis (EFA) is used on potential scale items to see if any emergent scale factors can be made from the data. EFA helps establish construct validity as well as internal consistency reliability (DeVellis, 2016). Preliminary examination before factor analysis can begin depends on the factorability of the data. This is determined through inspection of the correlation matrix, Bartlett’s test of sphericity, and a Kaiser-Meyer-Olkin (KMO) test to assess the Measure of Sampling Adequacy (MSA). Adequate correlations for all scale variables were examined, with most correlations above the threshold of 0.30 with some exceptions that will be discussed shortly. Additionally, Bartlett’s test of sphericity produced significant results ($p < 0.000$), and the KMO resulted in a sufficient value (MSA = 0.96) of above 0.60 to continue with the analysis. The data exist as item-level only at this stage and to convert them to factor level data, this study performed principal axis factoring and maximum likelihood. All 41 items were introduced to the EFA through the Psych R package. This package has many statistical tools for social and psychological sciences and is continually updated based on new research.

A Parallel Analysis (PA) tool was used to run an initial factor model using Maximum Likelihood (ML) factor method and a scree plot using Principal Axis Factoring (PAF). The correlations were found using a polychoric function instead of a standard Pearson coefficient due to the ordinal measurements. This treatment is recommended for calculating a reliability measure in non-continuous data to reduce attenuation (Pituch & Stevens, 2015). The simulated data was made with 100 iterations, and eigenvalues were found after estimating communalities instead of finding eigenvalues after the first factor. Eigenvalues measure the variance explained by a factor, essentially the factors efficacy in the scale. This procedure alone often recommends too many factors and should be combined with one of the other approaches (Carpenter, 2018). The PA found three factors based on the initial analysis, with all items included even after using a cutoff value of 0.32 factor loading (Table 2). Additionally, a scree plot displayed how the first factor overwhelmingly outperforms the second and third factors. After rotating the factors using an oblimin rotation procedure, which allows items and factors to covary instead of isolating them, the three factors contributed to 50% of the explained variance with the first factor explaining 26% ($M = 3.85$, $SD = 0.82$, $\alpha = 0.95$), the second factor explaining 12% ($M = 3.16$, $SD = 0.95$, $\alpha = 0.89$) and the third explaining 12% ($M = 3.72$, $SD = 0.79$, $\alpha = 0.89$). The three-factor model 1 was successful in finding the structure of the data. However, upon qualitative analysis of each item's content within the three factors, it emerged that one of the factors was formed solely due to the question wording. Every item that was negatively worded in the survey was found in the second factor. This factor structure is most likely not due to the items pointing to a specific part of the latent variable. Thus, the first three-factor model could not be justified as a reliable measure of the latent variable.

	Factor				
	1	2	3	H^2	U^2
seems insincere about their intentions.	0.90			0.61	0.39
is honest in communicating with others.	0.78			0.65	0.35
is ethical about their research.	0.74			0.58	0.42
shares open access of information to all.	0.72			0.49	0.51
is clear to understand when they communicate with others.	0.71			0.50	0.50
allows others the opportunities to share their opinions.	0.69			0.57	0.44
is competent in their field.	0.67			0.43	0.57
is straightforward in communicating with others.	0.66			0.56	0.44
communicates together for mutual betterment.	0.65			0.48	0.52
made me think about future decisions that could be informed by science.	0.65			0.56	0.44
is well educated.	0.60			0.46	0.54
is empathic in understanding other people's feelings.	0.58			0.38	0.63
shares common ground of communication with others.	0.56			0.50	0.51
recognizes the unique value of other people's opinion.	0.55			0.49	0.51
is not deceptive in interpreting others opinions.	0.54			0.30	0.70
encouraged interaction.	0.53			0.49	0.51
genuinely commits to the conversation with others.	0.51			0.56	0.44
invites other people to communicate.	0.47			0.38	0.62
tries to understand problems from other people's perspectives.	0.46			0.34	0.66
tries to establish that others correctly understood information.	0.43			0.40	0.60
understands how people think about the work that scientist do.	0.43			0.59	0.41
was excited to talk about their discoveries.	0.42			0.54	0.46
gave everyone the opportunity for follow up questions.	0.41			0.55	0.46
does not consider other people's opinions as worthy considerations.		0.79		0.64	0.36
is hard to talk to. (R)		0.71		0.60	0.40
isn't considerate of others. (R)		0.71		0.53	0.47
seems insincere about their intentions. (R)		0.70		0.46	0.54
can't deal with diverse perspectives effectively. (R)		0.69		0.48	0.52
doesn't share the intent of communication. (R)		0.69		0.52	0.48
does not accommodate other people's feedback. (R)		0.66		0.44	0.56
didn't present information that felt close to home. (R)		0.65		0.43	0.57
changes their mood when introduce to different opinions. (R)		0.56		0.32	0.68
can't estimate how others might feel in the moment. (R)		0.49		0.23	0.77
demonstrated the topic to me.			0.82	0.68	0.32
created an opportunity for me to interact with the topic.			0.67	0.55	0.45
showed an interest in learning from my community.			0.65	0.58	0.42
spent a lot of their time with me.			0.52	0.37	0.63
compared the topic with something else I already understood.			0.52	0.53	0.47
was excited to share their findings with me.			0.49	0.61	0.39
presented new information to me.			0.44	0.47	0.53
framed things so that they made more sense for me.			0.41	0.53	0.47
Percent (%) of variance explained	26	12	12		

Table 2. Model 1 Exploratory factor analysis results

A second model was created using only items positively worded in the survey to account for the falsely labeled factor. Items loaded onto factor 2 in model 1 were most likely due to measurement error in item wording and are not included in any further models. This left the model with 31 items. The same procedure described above was conducted on the 31-item positive model, and the initial PA indicated a 2-factor model with much the same structure as the first and third factors as model 1 described above. The factors were rotated, and total variance explained was recorded at 50% with the first factor containing 33% (M = 3.85, SD = 0.80, α = 0.95) and the second containing 17% (M = 3.75, SD = 0.80, α = 0.92). All 31 items were included in each factor with a cutoff value set at 0.32 for factor loadings (Table 3). Initial qualitative analysis of the 2-factor, positive items only, model indicated heavy overlap between theoretical dimensions and the diminishing impact of the second factor. Due to this diminishing value and desire for a more parsimonious structure, a third PA was conducted with only one factor. This factor structure still explained a similar amount of variance within the model at 47% (M = 3.70, SD = 0.75, α = 0.96). Factor loadings for the one-factor model compared to the two-factor model were still very similar. All items in model 2 were still present in model 3 with just one factor. The qualitative item analysis of model 3 indicated an even spread of all theoretical dimensions proposed in the literature and no abnormalities were present (Table 4).

	Factor 1	Factor 2	H^2	U^2
demonstrates fairness towards others.	0.93		0.60	0.40
is honest in communicating with others.	0.80		0.65	0.35
is clear to understand when they communicate with others.	0.74		0.49	0.51
is ethical about their research.	0.73		0.58	0.42
is straightforward in communicating with others.	0.71		0.55	0.45
is competent in their field.	0.70		0.43	0.57
shares open access of information to all.	0.68		0.48	0.52
communicates together for mutual betterment.	0.68		0.49	0.52
made me think about future decisions that could be informed by science.	0.67		0.56	0.44
is well educated.	0.66		0.45	0.55
shares common ground of communication with others.	0.62		0.49	0.51
allows others the opportunities to share their opinions.	0.61		0.55	0.45
encouraged interaction.	0.55		0.49	0.51
genuinely commits to the conversation with others.	0.52		0.55	0.45
recognizes the unique value of other people's opinion.	0.52		0.49	0.51
is empathic in understanding other people's feelings.	0.51		0.36	0.64
tries to understand problems from other people's perspectives.	0.51		0.34	0.66
is not deceptive in interpreting others opinions.	0.50		0.29	0.71
tries to establish that others correctly understood information.	0.48		0.40	0.61
invites other people to communicate.	0.46		0.38	0.62
was excited to talk about their discoveries.	0.45		0.54	0.46
demonstrated the topic to me.		0.82	0.65	0.35
showed an interest in learning from my community.		0.77	0.59	0.42
created an opportunity for me to interact with the topic.		0.70	0.55	0.45
spent a lot of their time with me.		0.64	0.34	0.67
compared the topic with something else I already understood.		0.60	0.52	0.48
was excited to share their findings with me.		0.48	0.60	0.40
gave everyone the opportunity for follow up questions.		0.48	0.53	0.47
presented new information to me.		0.46	0.47	0.53
framed things so that they made more sense for me.		0.43	0.53	0.47
understands how people think about the work that scientist do.		0.42	0.59	0.41
Percent (%) of variance explained	33	17		

Table 3. Model 2 Exploratory factor analysis results

	Factor		
	1	H^2	U^2
is honest in communicating with others.	0.78	0.61	0.39
was excited to share their findings with me.	0.76	0.58	0.42
understands how people think about the work that scientist do.	0.76	0.57	0.43
made me think about future decisions that could be informed by science.	0.75	0.55	0.45
is ethical about their research.	0.74	0.55	0.45
genuinely commits to the conversation with others.	0.74	0.55	0.45
allows others the opportunities to share their opinions.	0.74	0.54	0.46
was excited to talk about their discoveries.	0.73	0.54	0.46
is straightforward in communicating with others.	0.73	0.53	0.47
framed things so that they made more sense for me.	0.72	0.51	0.49
gave everyone the opportunity for follow up questions.	0.72	0.51	0.49
recognizes the unique value of other people's opinion.	0.70	0.49	0.51
encouraged interaction.	0.70	0.49	0.51
demonstrates fairness towards others.	0.70	0.49	0.51
demonstrated the topic to me.	0.70	0.48	0.52
shares common ground of communication with others.	0.69	0.48	0.52
communicates together for mutual betterment	0.68	0.46	0.54
compared the topic with something else I already understood.	0.68	0.46	0.54
shares open access of information to all.	0.67	0.45	0.55
presented new information to me.	0.67	0.45	0.55
is clear to understand when they communicate with others.	0.67	0.45	0.55
showed an interest in learning from my community.	0.67	0.44	0.56
created an opportunity for me to interact with the topic.	0.66	0.44	0.56
is well educated.	0.66	0.43	0.57
tries to establish that others correctly understood information.	0.63	0.40	0.60
is competent in their field.	0.62	0.39	0.61
invites other people to communicate.	0.62	0.38	0.62
is empathic in understanding other people's feelings.	0.60	0.35	0.65
tries to understand problems from other people's perspectives.	0.58	0.34	0.67
is not deceptive in interpreting others opinions.	0.53	0.28	0.72
spent a lot of their time with me.	0.48	0.23	0.77
Percent (%) of variance explained	47		

Table 4. Model 3 Exploratory factor analysis results

Further exploration was done within Model 3 by choosing items from each of the 12 theoretical dimensions with the highest factor loadings per dimension. The same procedures were performed with those 12 items in Model 4. All items in the model were extracted on one factor with loadings above the cutoff value of 0.32. The lowest loading was recorded at 0.52 and the proportion of variance explained was calculated at 51% (M = 3.82, SD = 0.80, α = 0.92) outperforming all other models previously examined (Table 5).

	Factor		
	1	H^2	U^2
understands how people think about the work that scientist do.	0.78	0.61	0.39
is honest in communicating with others.	0.77	0.59	0.41
was excited to share their findings with me.	0.77	0.59	0.42
is ethical about their research.	0.73	0.53	0.47
allows others the opportunities to share their opinions.	0.73	0.53	0.47
recognizes the unique value of other people's opinion.	0.73	0.53	0.47
shares common ground of communication with others.	0.70	0.50	0.50
communicates together for mutual betterment.	0.69	0.48	0.52
gave everyone the opportunity for follow up questions.	0.69	0.48	0.52
framed things so that they made more sense for me.	0.68	0.47	0.53
is clear to understand when they communicate with others.	0.68	0.46	0.54
tries to understand problems from other people's perspectives.	0.58	0.34	0.66
Percent (%) of variance explained	51		

Table 5. Model 4 Exploratory factor analysis results

CONFIRMATORY FACTOR ANALYSIS

Once factors have been established using the EFA procedures, the next step in scale development is to take that factor structure and use it in a Confirmatory Factor Analysis CFA. A CFA is used to support a factor structure's fit on the intended latent variable and is often used to continually validate previously created scales in new contexts (Pituch & Stevens, 2015; Worthington & Whittaker, 2006). Model 4 from the EFA will be used on the second sub-sample to establish construct validity and reliability due to its parsimony and ability to represent the full dimensional structure of the latent variable.

CFA is a subset of Structural Equation Modeling. This is a popular tool to use in multivariate statistics when path structures of data need to be analyzed. CFA is similar to these path analyses but usually uses fewer dependent variables and more independent variables representing the latent variables being measured. Multiple different fit indices will evaluate how well the factor relates to a latent variable. These indices are used to measure how well the measured independent variables in the survey represent the latent dependent variable under investigation. Multiple psychometric researchers recommend a combination of incremental and absolute fit indices (Pituch & Stevens, 2015). Incremental fit indices measure the improvement in a model's fit to the sample by comparing a specific structural equation model to a baseline. Absolute fit indices can help explain how well a structural equation model reproduces the data. The most recommended indices are the Comparative Fit Index (CFI) and Turner-Lewis Index (TFI) for incremental and the Root Mean Square Error of Approximation (RMSEA) and Standardized Root Mean Square Residual (SRMR) for absolute fits. Also recommended is a chi-square for an overall fit test of the theoretical model to the data. Model 4 presented TLI and CFI measures over the recommended level of 0.09 ($CFI = 0.94$, $TLI = 0.93$), and the absolute fit indices of RMSEA produced adequate fit ($RMSEA = 0.8$, $p < 0.05$) while the SRMR produced a measure of good fit ($SRMR = 0.05$). The chi-square statistic was not significant ($\chi2 = 116.90$, $df = 54$, $p < 0.000$), but together the fit indices demonstrate overall construct validity. Item level standardized and unstandardized loadings can be found in Table 6.

	Loadings	SE	Std. loadings	R^2
communicates together for mutual betterment.	0.72	0.03	0.75	0.51
is honest in communicating with others.	0.79	0.04	0.73	0.62
is ethical about their research.	0.72	0.04	0.73	0.52
shares common ground of communication with others.	0.70	0.04	0.72	0.49
understands how people think about the work that scientist do.	0.72	0.04	0.70	0.52
is empathetic in understanding other people's feelings.	0.73	0.04	0.70	0.53
framed things so that they made more sense for me.	0.70	0.04	0.67	0.48
is clear to understand when they communicate with others.	0.69	0.04	0.65	0.48
allows others the opportunities to share their opinions.	0.66	0.04	0.65	0.43
was excited to share their findings with me.	0.61	0.05	0.60	0.37
is straightforward in communicating with others.	0.59	0.05	0.58	0.35
gave everyone the opportunity for follow up questions.	0.57	0.06	0.50	0.32

Note: CFA only performed on a randomly split-second subsample of n = 202
All items significant at p < 0.00

Table 6. Standardized factor loadings and communalities from CFA

CONVERGENT AND DISCRIMINANT VALIDITY

Model 4 supported construct validity measures through the fit indices, but a common step for improving overall validity is to compare the newly created scale to other previously validated measures through convergent and discriminant validity (DeVellis, 2016). Convergent validity is measured by comparing a scale to a similar concept. These two concepts should be correlated based on their latent construct similarities. Discriminant, sometimes called divergent, validity is the same process but with conceptually different items. The variables used for discriminant validity should not correlate. This study used eight variables to establish external validity described in the above measures section.

The same procedure performed in the CFA is used for establishing convergent and discriminant validity. Instead of measuring item or factor fit onto a latent variable, the newly validated scale is compared with other scales. The chi-square, CFI, TLI, RMSEA, and SRMR fit indices were used to compare the SCER scale to the latent variable structure for each of the eight validity measures independently. The first comparison concerned the SCER scale and the items that reflected why someone follows news and science information. The incremental fit indices presented good fit measures above 0.90 (CFI = 0.92, TLI = 0.91) and the absolute fit indices produced measures above the acceptable threshold (RMSEA = 0.62, SRMR = 0.05). RMSEA measure demonstrates a significant measure of fit, but the chi-square statistic did not ($\chi 2$ = 268.58, df = 151, $p < 0.000$). The SCER scale and why people follow science news and information measure similar constructs according to the data in this study.

Second, the SCER scale was compared to a single score that reflected respondents' science literacy. The overall science literacy score and the SCER scale had good fit on all indices used (CFI = 0.94; TLI = 0.92; RMSEA = 0.07, $p < 0.05$; SRMR = 0.05). The chi-square test for overall fit was not significant ($\chi 2$ = 131.04, df = 65, $p < 0.000$), but overall fit indices indicate the latent structure of SCER is positively related to science literacy. The next scale used for external validity was the science career interest measures. These items had a similar overall fit to the science interest scale with the SCER scale. The two incremental fit measures for CFI and TFI were close to their target level but not over the expected 0.90 (CFI = 0.89, TLI = 0.87) and the absolute fit indices recorded an adequate fit (RMSEA = 0.08, $p < 0.000$) and acceptable fit (SRMR = 0.06). The chi-square statistic was not significant ($\chi 2$= 303.95, df = 134, $p < 0.000$). The hypothesized relationship between the science career interest scale is correlated with this study's measure for SCER based on all fit indices.

A single item score for both promise in science and funding for science were also compared to the model. The single measure for promise in science found acceptable fit for incremental indices (CFI = 0.93, TLI = 0.92) as well as adequate fit for both absolute indices with RMSEA significance (RMSEA = 0.07, $p < 0.000$; SRMR = 0.05). The chi-square test for overall fit with SCER was not significant ($\chi 2 = 134.71$, df = 65, $p < 0.000$). The single measure for favor in government funding for science also demonstrated acceptable fit from all indices and global fit was significant (CFI = 0.94; TLI = 0.93; RMSEA = 0.07; SRMR = 0.05; $\chi 2 = 124.17$, df = 65, $p < 0.000$).

The next two measures concerned participants' cultural worldviews. The communitarian vs individualistic scale failed to meet fit standards on both incremental and absolute fit indices and non-significant chi-square test (CFI = 0.84, TLI = 0.81, RMSEA = 0.09, SRMR = 0.09; $\chi 2 = 339.75$, df = 134, $p < 0.000$). The hypothesized relationship gains partial support but does not meet the fit requirements needed for the latent variable's intended relationship. Similarly, the egalitarian vs hierarchical scale did not meet fit measures for any of the indices or the chi-square test (CFI = 0.81, TLI = 0.78, RMSEA = 0.11, SRMR = 0.13; $\chi 2 = 430.18$, df = 134, $p < 0.000$). This is not enough to support the hypothesized relationship with SCER.

Finally, the measure for tendency to believe in conspiracy theories, or conspiracist ideation, was used to establish discriminant validity. This variable was found to meet all fit standards of incremental and absolute fit but failed a significant chi-square test (CFI = 0.93, TLI = 0.91, RMSEA = 0.64, SRMR = 0.05; $\chi 2 = 216.37$, df = 118, $p < 0.000$). However, because items were coded for higher levels to indicate more conspiracist ideation, this relationship, given the positive regression coefficient, does not reaffirm the hypothesized relationship with SCER.

Overall, the results indicate a simple 12-item, one-factor scale for Science Communication Engagement Response (SCER) that has reliability, construct and content validity, and convergent and discriminant validity with a handful of measures related to the latent variable (Figure 4). These results are an essential first step in quantitatively identifying ‘quality’ science engagement based on audience perceptions. Discussion and implication of these findings will continue in the following section.

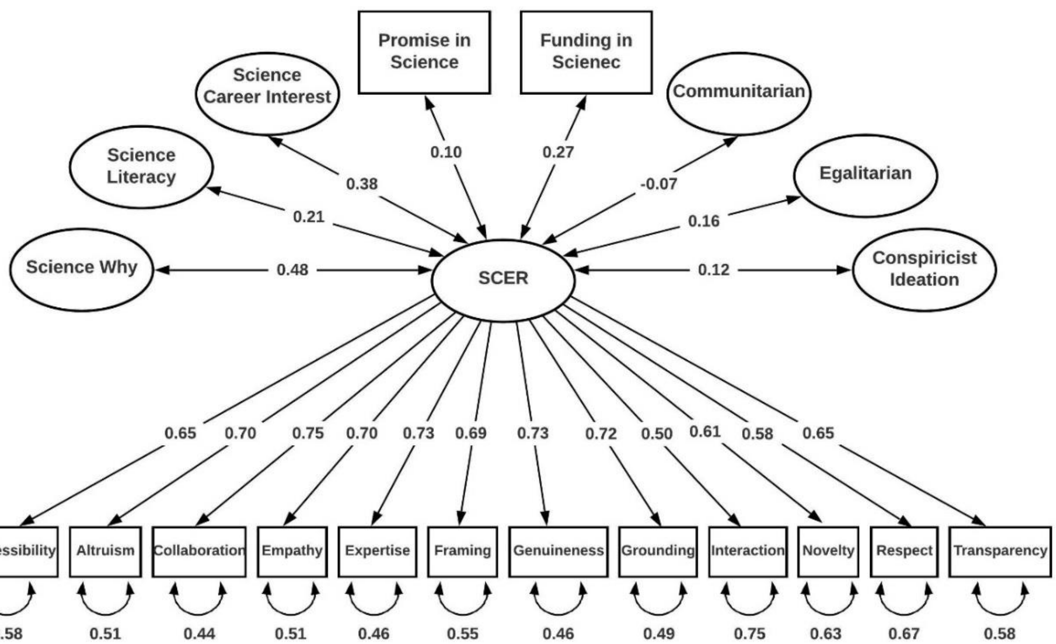

Figure 4: SCER model with standardized factor loadings (all at $p < 0.05$), item theoretical labels, standardized residual variances, and convergent/discriminant validity variables with standardized correlation coefficients.

Chapter VI: Discussion

This study aimed to connect different communication research areas to develop a measurement tool for Science Communication Engagement Response (SCER). The core use of this tool is to help quantitatively gauge the effectiveness of a science communicator shortly after an engagement activity. Activities that share new information and nurture positive ideas about science like social media Q&As, live demonstrations in person or through video chat software, videos, podcasts, or others. These engagement activities lack a quantitative evaluation measure rooted in science communication research, without such a measure scientists are left in the dark on the impact left on the audience. The twelve theoretical dimensions in science communication engagement loaded onto one factor through 12 items, one for each dimension. This scale produced acceptable measures across multiple fit indices and acceptable comparisons to convergent and discriminant validity. Science communication actors and outcomes can be evaluated with better precision through this scale based on the theoretical foundations in science communication, communication engagement and other strategic communication scholarship. However, the findings presented here are only a first step. More research is still needed to further hone and sharpen this scale into the helpful tool it can become. This section will first discuss the findings mentioned in the results section, then discuss the potential uses and possibilities for the scale. Finally, this section will conclude with implications and further directions of the research started here.

FINDINGS

In this section I discuss the results of the scale development process for SCER. The exploratory factor analysis is discussed and the evolution from model 1 to the final model 4. Then I describe how the confirmatory factor analysis confirms the factor structure of model 4 found in the exploratory factor analysis. Finally, a discussion of convergent and discriminant validity related to the conceptually similar and dissimilar variables compared to SCER.

Establishing the Scale Structure

The final model contained one item from each of the 12 theoretical dimensions connected to science communication engagement. These 12 items loaded onto one factor through an iterative process from four models created in the exploratory factor analysis. However, all 41 items that made the original list did not all have a fair shot at the final scale. The reverse wording on ten items led the factoring process to bundle them together in their own factor. Scale developers warn against this method when creating a scale, but survey techniques also encourage reverse-scored items to improve results and limit acquiescence (DeVellis, 2016). Consequently, including reverse-scored items seemed to have done more harm than good, and model 1was not used. It is unlikely that wording the items the same as the others would have helped the hypothesized factor structure. Even with eigenvalues and the scree plot for Model 1, the first factor comprised most of the final one-factor model (Model 4). The first factor in every model also takes up more than half of the proportion explained.

Following the removal of all reverse coded items, Model 2 was created through the same parameters using parallel analysis to simulate 100 different data samples based on the first split-sample used for the exploratory stage of scaled development. Parallel analysis, as well as the minimum average partial, suggested a two-factor structure for Model 2. This two-factor structure with the 31 non-reversed items presented a similar factor loading proportion of variance as Model 1 where the first factor makes up the majority of variance explained. The two factors were allowed to covary during their rotation due to the nature of the hypothesized factors. All theoretical dimensions of SCER covary with each other, and there is no science engagement area separated from any other. This melding of variables and ideas is why it’s so hard to find a solid answer for “what is engagement.” The term means so many different things to so many people, but they revolve around a central idea. The dynamic multidimensional relational concept from psychological and behavioral attributes of connection, interaction, participation, and involvement designed to achieve an outcome (Johnston & Taylor, 2018).Allowing the factors to share variance in the scale development process reflects this conceptual linking. Upon closer look at each factor's items in Model 2 there was a high overlap between theoretical dimensions in both factors. Dimensions used in the OPDC scale dispersed between the two factors in model 2. This is reassuring because it enforces the idea that science communication engagement is different from other engagement types. If items from the OPDC scale loaded onto their respective factors (mutuality and openness), then that would indicate the latent variable structure was closer to organizational dialogic communication with a hint of science. These results conclude that science communication engagement is a sperate latent variable that exhibits influence on items independently of other scales. A context adjacent scale would not be appropriate for science communication scale with simple item word changes. Additionally, each dimension, interaction, science communication goals and objectives, and scientific expertise, loaded on the two factors. The factors were not qualitatively distinct from each other based on their theoretical structures. A third model examined dimensional overlap through an EFA with one factor.

The third model was the result of the iterative exploratory phase coupled with poor results of Model 2. Relying only on empirical analysis for scale creation is not recommended, and scale developers are encouraged to find a structure that makes sense through data and theory (Carpenter, 2018; DeVellis, 2016; Worthington & Whittaker, 2006). Model 3 explored a one-factor solution with all 31 positively worded items included in Model 2. The exploratory analysis Model 3 produced similar variance explained and retained all 31 items with a factor loading cutoff value of 0.32. The factor loadings were almost identical to those recorded in Model 2 and justified the one-factor model even with empirical results indicted by the VSS and MAP calculations recommended otherwise. The scree plot and PA simulations also presented similar results to Model 2, just with one less factor. Overwhelmingly, the first factor of Model 1 and 2 explained over half of the variance for the models' totals (~ 50%). In Model 3, the total variance explained only dropped down a few percentage points for a final variance of 47%. A qualitative examination of the items in Model 3 proved to contain all 12 theoretical dimensions. A final model analyzed a potential one-factor solution with one item per dimension for the highest loading reported in Model 3.

Model 4 contained just the bare bones of the scale structure found in Model 3. There were 31 items loaded across one factor from 12 dimensions. Model 4 looked at the factor structure of the highest factor loadings for each dimension from model 3 resulting in 12 items total. This model was planned as an abbreviated model during data analysis due to its smaller size and adherence to theory. However, throughout the confirmatory and convergent discriminant validity phases of analysis, Model 4 outperformed Model 3. The exploratory factor analysis for Model 4 presented theoretical and statistical results that reinforced this decision. There was no substantial loss of variance, and theoretical dimension diversity was still maintained with the 12-item, one-factor Model 4. When Model 4 was introduced in the confirmatory analysis using the second split sample the results were just as encouraging. The incremental fit indices both presented good fits above 0.90 and both absolute fit measures at adequate and acceptable. These measures communicate the scale's construct validity with the latent variable.

Scale Confirmation and Comparison

Following the confirmatory analysis of Model 4 the validated scale was then measured against previously validated measurements similar to the construct measured by the SCER scale. The same fit indices assessed convergent and discriminant validity (CFI, TLI, RMSEA, and SRMR) with other scales and observed measures. Science interest established convergent validity with a positive correlation and adequate fit for incremental and absolute indices. Further comparisons found similar fit results for the composite score of science literacy and the science career interest scale. Two observed measures compared the SCER scale to promise in science and funding for science. These two items found partial support in comparison to SCER due to their low fit indices. These measures produced inconsistent comparisons most likely due to their uni-dimensional structure. Two cultural worldview scales contributed to additional convergent validity. Positive correlations indicate communitarian and egalitarian subscales pair well with SCER. The incremental fit measures did not find a good fit, but the absolute fit indices maintained adequate fit. These subscales acted as both convergent and discriminant validity. Their opposite worldviews (individualistic and hierarchical) reflected by lower scores on the scale indicate poor fit with worldviews with less positive beliefs in science (Kahan et al., 2012).

Finally, this study used a measure of conspiracist ideation to establish discriminant validity. This measure should have been negatively correlated with the SCER scale due to higher conspiracist ideation measures reflecting higher tendencies to believe in conspiracy theories. However, the correlation was positive indicating a mismatch between the hypothesized conceptual relationship. Although the correlation was low (B = 0.12), ideally, the two latent variables would be negatively correlated. The fit measures for conspiracist ideation also indicate poor fit for incremental indices and adequate to acceptable fit for absolute indices.

Ideally, respondents with positive experiences with scientists due to high science communication engagement would have lower scores for conspiracist ideation. Conspiracy theories offer simplified explanations of reality and are crafted to tolerate levels of uncertainty (Byford, 2011). Consumption patterns on social networking sites for science and conspiracy theory content are similar (Vicario et al., 2016). Past research has seen conspiracist ideation and other measures of science at odds with each other

(Lewandowsky, Ecker, & Cook, 2017). When exploring measures for conspiracist ideation related to sample demographics, no clear patterns emerged. There were slightly higher scores with older participants. Respondents who recorded ages above the median (75) had only slightly higher conspiracy beliefs (M = 3.35, SD = 0.90) compared to the full sample (M = 3.26, SD = 0.93). This difference was not enough to explain the results. Additionally, there was no difference in participants with higher education levels. Respondents with at least some college or less (M = 3.28, SD = 0.88) recorded similar beliefs in conspiracy theories compared to respondents with a college degree or more (M = 3.24, SD = 0.97). The same similarity continues with more conservative (M = 3.27, SD = 0.91) and more liberal respondents (M = 3.26, SD = 0.94). One possible explanation is the positive skewness of the items across convergent and discriminant validity variables and the number of questions in the survey. These items were one of the last listed before the scale items that were prompted by a qualitative response. Respondents had to get through screener questions and seven other variables before finally getting to the questions related to conspiracies. There is a high likelihood that by this time most respondents experienced survey fatigue or acquiescence, a type of response bias where respondents believe they should choose the correct answers. Since conspiracy belief items were oriented so that higher scores indicated higher conspiracy beliefs, respondents who read through previous questions and saw a positive desirability bias could have exhibited a carryover effect to the final set of pre-scale questions. However, this explanation puts more faith into theory than what the data says. Results still indicate a lower than hypothesized relationship with SCER and conspiracist ideation.

Chapter VII: Limitations

The findings expressed above are not without their limitations. Things to consider when looking through the implications discussed in the next section include the high average age of the sample, skew towards democratic political affiliation, and the reverse coded items excluded from models 2 – 4. These items should be noted for future research and practice with SCER.

The screening questions at the start of the survey used to gather quota based on the last U.S. census data included race and ethnicity, gender and residency questions. There was no question used to screen respondent's age. This led the sample to have a higher average age (M = 67) than the average age of the U.S. (37.2). The standard deviation for respondent age was 24.82 indicating a varied distribution of ages throughout the sample. However, this is still more than the ideal age range for the study given the focus on census data for screening. Future research should look to investigate lower age ranges. Additionally, screening questions were not included for political party affiliation. The current analysis does not look into party affiliation as a validation variable, however there is evidence that suggests party affiliation has an influence on overall science beliefs (Kahan, Landrum, Carpenter, Helft, & Hall Jamieson, 2017; Scheufele & Krause, 2019). Future research should be aware of the high distribution of respondents who call themselves Democrats (49.3%) versus Republicans (19.1%).

Survey questions are often reverse scored so that respondents are encouraged to read through question wording. This helps respondents decrease their chances of choosing the same answer choice for a set of questions and is a common practice in survey research. However, reverse coding is warned for scale creation because it often causes more harm than good. Items with similar wordings can have a tendency to group together during factorization (DeVellis, 2016). The current survey included reverse scored items on validation variables and scale items to encourage respondents to answer based on item wording. During the initial EFA in model 1, reverse scored items loaded onto their own factor. This was due to the item wording and not any underlying theoretical dimensions. Reverse scored items were excluded from each subsequent EFA model and did not show up in the final scale. Unfortunately, excluding these items means that any potential additional factor structure found by including them is lost in the current analysis. The one factor structure is still encouraging for future research and presents a parsimonious scale that represents all theoretical dimensions in science communication engagement.

Chapter VIII: Implications and Future Research

IMPLICATIONS

The creation of this scale builds on more than a decade of past research into scientists' willingness to engage with the public. This tool looks at audience response to public engagement activities so the quality of those activities can be measured. This section looks at this past research in relation to the SCER scale and how the measurement can improve current ideas of PES. Then I describe how the scale can be inserted into a number of existing models as an evaluation tool scientists can use to improve their effectiveness.

SCER and Research in Science Communication

The SCER scale builds on past quantity measurements in science communication to establish a quality measure for engagement within that communication. Since the deficit model's onset to more dialogic or two-way models used today, science communication has relied chiefly upon convenience measures for the concepts of interest. Concepts like scientists' willingness to engage initially sparked my interest in scale development. This measure has been the focal dependent variable in numerous studies (J. C. Besley, Dudo, Yuan, et al., 2018; Copple et al., 2020; Dudo et al., 2018). Willingness to engage has been used as a proxy for behavior as an intention to behave. Intention variables are prevalent in research using Theory of Planned Behavior or the Integrated Behavioral Model that positions efficacy, norms, and attitudes as independent variables. Science communication studies using this measurement often ask one question to survey respondents about "how willing would you be to participate in any science engagement activity with adult non-scientists." Although this is a good question for what it is, and studies often use this item to include their preferred definition of public engagement with science and offer examples, this is still a single-item measure for a complex idea we call engagement. Even when researchers use a single-item measure for willingness, the same research uses multi-item measures for all the model's main independent variables. Not to say that some concepts can't be measured with a single item, but they usually lead to misclassifications (Millner, Lee, & Nock, 2015). With everything we know about science communication and engagement, a single-item measure lacks the fidelity we can get from such a complex concept.

Science communication has several different moving parts from the scientist to the end audience and people in between like journalists and science communicators to the different contexts, platforms and engagement activities. Much of the work done by science communication researchers focuses on enabling scientists to communicate more. This is why the Theory of Planned Behavior has been such a popular model: its primary function is to help explain, predict, and ultimately aid in the changing of behaviors (Montaño & Kasprzyk, 2008). Ongoing research has found things like formal training, more confidence, and more positive attitudes help scientists to increase their willingness to engage (Copple et al., 2020). However, scientists and practitioners lack a theoretically driven evaluation of their communication activities and what constitutes high-quality engagement and low-quality engagement? The SCER scale is designed to help grapple with this question. The scale is a multidimensional measure of the complex concept of science communication engagement. This scale takes what we know from multiple areas (science communication, public engagement with science, public relations theories, and communication engagement) and combines them for a 12-item measure that presents one way to help gauge the efficacy of PES activities.

Evaluating PES Through SCER

PES has made great strides already noted in the literature review with different models and measurements close to the latent variable represented by the SCER scale. However, these models and measures don't include empirical tools that science communicators can use to improve their PES endeavors. The AAAS theory for change has all the right pieces in place for a strong representation of high-quality science engagement (American Association for the Advancement of Science, 2016). The guidelines discussed throughout the document focus on practitioner use and align with the most recent literature in science communication. However, the one thing the model is missing is a useful measurement tool that practitioners and science communicators can use to gauge how well they are connecting with their audience. Changing perceptions, affect, behaviors, and identities with science can be easily evaluated in the theory for change through SCER. Scientists can use the 12-item scale to evaluate their ability to change affect by highlighting the empathy, altruism and genuineness items in the scale ("is empathetic in understanding other people's feelings.", "understands how people think about the work that scientist do", and "is honest in communicating with others."). The Dialogic Model is also closely aligned with the current literature (House of Commons Science and Technology Committee, 2017). This model hinges public engagement on two-way, proportional dialogue with science and the public for better decision making through policy. The Dialogic Model represents a framework that increases positive attitudes toward science, improve communicating uncertainty with the public, and maintain dialogue with the public about policy changes, including the SCER scale can help measure those changes over time. For example, focusing on collaboration ("communicates together for mutual betterment"), grounding ("shares common ground of communication with others"), and interaction ("gave everyone the opportunity for follow up questions") items offers better evaluation of policy collaboration between scientists and the public. The inclusion of the SCER scale into the above two models will help present an accurate reflection of what works and what does not when it comes to communication strategies. The SCER scale is meant to measure audience response to these engagement activities and evaluate their effectiveness.

The SCER scale is also more suitable for certain situations compared to the two other measurement tools mentioned previously. The DEVISE toolkit contains a measurement for engagement; however, it only includes behavioral engagement for citizen scientists involved in a research project with other research scientists. Behavioral engagement is an essential part of the communication engagement model discussed in the literature review, but it is only part of the picture. This scale neglects to measure any attitude or emotional component of engagement (Johnston & Taylor, 2018). One potential outcome from only using the behavioral scale could be a citizen-scientist enjoys the tasks given to them for the project (recording bird watching, helping tag aquatic animals, or scouting the forest floor for plant types). This would record high scores on the DEVISE behavioral engagement scale But, the scientist may seem disinterested in what the citizen-scientist had to say and didn't seem excited to be there. The citizen-scientist might feel like the scientist didn't care if they helped or not and may not be back for future research help. This hypothetical situation would leave a high score on the behavioral engagement scale in the DEVISE tool kit but a lower overall score on the SCER scale. Another scale recently published is closer to a holistic measure of science communication engagement but has a different purpose than the SCER scale. The Outcome Expectation Scale measures the external or response efficacy a scientist has about public engagement activities (Peterman et al., 2017). This variable has been a consistent contributor to research that measures the quantity of science engagement but, like many measurements currently in use, does not tell us enough about how the audience perceived their engagement efforts. True engagement may ultimately come from multiple different sources and methods, but if an audience responds negatively to an engagement activity, then it would help to know what area the scientists need to work on.

The SCER scale considers a generalized model of communication engagement instead of purely relying on science engagement research. This means that the scale collects ideas about behaviors, attitudes, and emotions related to engagement. In the Communication Engagement Model presented in Chapter 2 by Johnston and Taylor, establishing these mechanisms can lead to individual engagement outcomes like dialogue, advocacy, and interaction (2018). In this model, the authors see dialogue as an outcome. In the SCER scale, dialogue is a dimension represented by mutuality, the mutual confirmation of unique values in different views. This flip is due to how researchers and practitioners administer the scale. The scale should be issued shortly after an engagement activity, meaning that dialogic communication should have already happened and is not an outcome but part of the process. Continual dialogue from audience members to scientists and other members of the public is still an outcome linked to all science communication. Therefore, this scale differentiates dialogue as an outcome and dialogue as a process. The Communication Engagement Model continues to talk about community-level engagement which is harder to measure and not intended to be the central focus of this dissertation. This effort will help build up to community-level engagement by first ensuring and evaluating science communication engagement at the individual level as an experienced state. SCER is a scale that measures the internal mechanisms of individuals based off current scholarship and the outlined areas in the Communication Engagement Model.

The current orientation is for the SCER scale to measure engagement of audience members. After further validation studies, one potential use is to use the scale in place of the single measure of willingness to engage mentioned earlier. Instead of examples and definitions that vary across studies (Appendix A), this 12-item scale can represent what scientists are willing to do when measuring their intention to engage the public. If used in this way, scholarship will begin to develop a better picture of the types of science communication engagement scientists see as valuable. Ideally, they would value everything that scholars and researchers do, but scientists and science communication researchers think differently on the importance of some science communication objectives (Yuan, Besley, et al., 2019). Using this adapted scale on scientists can also reflect what scientists have done in the past more clearly. Instead of asking "what public engagement activities have you done in the last 12 months," researchers can ask questions with greater detail like: "How well have you demonstrated empathy with a public engagement audience in the past 12 months" or "On a scale from 1-5 how much do you agree with the following statement: Being transparent with non-scientists I communicate to is important to me." These implications have an overall benefit to numerous areas of science communication and PES research.

FUTURE RESEARCH

This section will help readers see a more precise picture of what future research with SCER looks like. The continual validity practices needed for a new measurement tool will be described through a planned study using a mulitrait-multimethod matrix. Then a study is described that will help SCER build validity through a comparison to some gold standard. This study will help establish criterion validity. Finally, SCER represents a general measure for science communication engagement, but contextual adaptation of the scale is described to better view a scientists' engagement across different media terrain.

Mutlitrait-Multimethod Matrix and Maximizing Validity

Further scale validation is essential. The content and construct validity demonstrated in the current analysis is only the start. Scales undergo a continuous validation process both through formal reliability and validation studies and outside authors that use the items and find similar results over time. The next step in scale validation is to conduct a Multitrait-Multimethod Matrix analysis with the scale (Campbell & Fiske, 1959). This methodology involves measuring more than one construct through more than one method. Each construct, or latent variable, is measured using two methods (some combination of survey, experiment, or interview) from two samples. Each cell would represent the combination of construct and method. This validation approach compares different methodology, samples, and variables at once, which helps maximize construct validity. The best way to demonstrate further validity through this design for SCER would be an in-person interview with one sample and a survey with the same stimulus for both methods. The stimuli would be a recording of a science engagement activity that represents low quality engagement and one that represents high quality. The difference between the two would be operationalized through the 12 items in the SCER scale. For example, demonstrating high quality engagement includes asking the audience questions or giving them the opportunity to ask questions. The video could showcase the scientist requesting questions from viewers (like in a comment section) or a scientist taking questions from an audience. Demonstrating interaction can include the scientist asking viewers to perform a task on their own or bringing in a non-scientist to participate in a task. The survey and interview would include randomized groups of both conditions (high and low engagement) and be asked the same questions in different format. The two would also include convergent and discriminant validity items like the ones included here. Addressing construct validity here includes comparing the two different methods for similar correlations between the SCER scale with high and low groups as well as the additional validity items.

A second follow-up study would include the addition of Item Response Theory (IRT) instead of the CTT used for the current analysis (Carpenter, 2018; DeVellis, 2016). IRT allows researchers to look at specific items within a scale and examine how items perform independently of individuals answering the questions. Like a bathroom scale measuring only the weight of an object and nothing else about it, IRT uncovers scale items that perform regardless of sample characteristics. IRT also helps researchers identify items that may lie on a continuum. This aspect is most interesting for SCER because of the theorized communication engagement hierarchy (Johnston & Taylor, 2018). The main reason for not using IRT in the current analysis is due to sampling limitations. IRT requires large heterogeneous samples or else reliability is lost. The sample used here was heterogenous but lacked a sufficient number of respondents for IRT to be beneficial.

Establishing Criterion-Related Validity Through TikTok

Research for validation is essential, but equally as important is research that examines the scale's predictability. Criterion-related validity is a measurement of how well a scale can predict a desirable result or a "gold standard" related to the variable (DeVellis, 2016). Criterion-related validity is a cousin of construct validity. Even though they both measure how well the scale can measure the latent variable, only criterion-related validity measures predictive power. Research that uses an experimental or quasi-experimental methodology can address this measure of scale effectiveness. One potential study is to partner with popular or upcoming science communication content creators on popular video platforms like YouTube or TikTok. TikTok would be an ideal platform for a research study because the user expectations are lower for production, content, and length of video than YouTube. TikTok is a much newer platform that has a 60 second limit to videos.

The content produced on the app uses music licensed by artists or another video's audio. TikTok encourages both imitation and replication of media content and contributes to an idea of imitation publics. Imitation publics are a collective of people whose connection comes from the shared ritual of imitating and replicating content (Zulli &

Zulli, 2020). This digital connectivity can drive positive attitudes through relationship capital from engagement activities, making TikTok a prime medium for PES. The platform was initially popular in China, launched in 2016 as Douyin and internationally as TikTok in 2017. It currently has 100 million monthly active users and more than 800 million monthly users worldwide (Sherman, 2020). This rise in popularity has created a space for a variety of genres, categories, and sub-categories within the platform. These categories are mostly driven by user actions saved in algorithms based on individual preferences. Suppose you scan through a user's videos because they focus on growing and maintaining indoor plants. In that case, the algorithm will remember that information, and all of a sudden, you're involuntarily part of "Plant-Tok." This happens with an endless list of user-generated genres for video games, makeup artists, and even science. Science communicators and scientists have created a space within the platform to have a captivated audience for science and educational content about all major STEM fields. One of the more popular science content creators on the platform is Hank Green (@hankgreen1). Most notably, Green created VidCon, the world's largest gathering for online video creation, and his educational online media company, Complexly, which produces content for science communication channels on various platforms. His popularity is most likely due to his embodiment of the science engagement principles and dimensions explicated in this dissertation. Green does a great job at making exciting content. He shows his passion for the topics talked about, and he displays empathy with ease at people on the platform looking for answers to complex questions like "Is ice a rock?" (spoiler: geologists categorize ice as a rock). Questions like these are one of the most interactive parts of any TikTok, and they help address the accessibility and transparency dimension of science communication. Unlike comments on YouTube, TikTok comments can be directly embedded onto a creator's video to respond to the comment or question. Users can also click the comment and find what video it originated from and what other users had to say in response to it. For these reasons, TikTok would be an ideal platform to test the predictive power of the SCER scale.

The research design would ideally involve 3-5 content creators on TikTok. The study would recruit them by sending individual messages to anyone within a network of science communicators on the platform. If a network or list of science communicators on TikTok isn't already created, the study would also include a network analysis to generate the list. Hank Green would be used as the initial starting point for the analysis and then branch from there to generate an initial list. This list would contain users that both create content and a lot that do not. One way to weed out the users who are not involved in content creation is to filter out users who have less than a specified number of videos on their profile that also follow other people within the network initially generated from Hank Green followers. Members on the list could reply with their interest in participating in a collaborative research study to help create videos for their audience. Students interested in science communication and video production could help the researchers and TikTok creators produce the videos and scripts. The videos would include as many dimensions from science communication engagement as possible. The team would hand over the videos to the content creators and maintain quantitative and qualitative digital metrics. Simultaneously, the videos would be reduced in production value (high, moderate, and low) while still maintaining the same content. These low production value videos would likely have no additional illustrations, comments, or editing techniques other than simple cuts to make the audio line up. These three video production layers would create the three conditions for each video: one video with minimal production, a second with moderate production, and a third with all production techniques used to create the final video given to the creators.

Stage two of the project would contain the experimental design, distribution, and analysis of responses. This study's measurements would include the SCER scale containing 12 items from the results detailed in this dissertation and other measures for condition checks like perceived production value and demographic variables. A survey distribution company would produce the sample for a representative sample of the American public. The strength of the sample and results would be imperative to establishing criterion-related validity. Respondents will receive one of the three videos from each creator involved in the project for a total of 5 videos (max number of content creators in the first stage of the project) ranging from high production to low production. Then respondents will be given the SCER scale to adequately measure engagement based on the current research of science communication engagement. A control condition will help compared to each condition. The control condition will have no focus on science or technology, and it won't feature an individual that could be confused for a scientist or science communicator (more than likely a cat video). Ideally, the scale should present results consistent across all groups regardless of production value. The low production science TikTok should be similarly engaging as the moderate and high production videos within each TikTok creator. Different individual preferences may appear between TikTok creators due to other factors like the creator's topic interest or likability.

If the scale has criterion validity, hypothesized results will generate similar engagement levels from the SCER scale regardless of video production condition. These findings would help explain that science engagement does not stem from sophisticated video production, but instead from the dimensions explored here. Additional construct validation with other engagement measures can be used to further establish validity for the scale. These results and further use from other researchers with the science communication community would make the SCER scale a solid measurement tool for evaluating audience members' engagement.

Contextual Scale Adaptations

SCER scale research can focus on contextualization and adaptation based on platform, topic, and any number of contextual differences. Even though SCER is meant to be a more general scale for engagement, it would be irresponsible for the scale to be thrown into any context without consideration of the platform, audience, and intended outcomes. SCER can help with overall evaluation of engagement, but as I have reported from expert interviews in the methods section, improving engagement relies on the communicator’s awareness of specific contexts. One adaptation of the SCER scale can be for face-to-face engagement. Questions about eye contact, active listening behaviors, and direct audience interaction can be supplemented or replaced based on the researcher or scientist's needs. Another adaptation can be for online dialogue between scientists and laypersons.

Reddit Ask Me Anything (AMA) are another popular platform for science communication. AMAs use a question-and-answer format within Reddit’s message boards where users can ask questions to scientists. Scientist AMAs have become more popular regardless, it seems, of the scientist participants' previous reputation. SCER can evaluate these interactions for engagement scores through a simple audience survey. Questions that measure digital engagement and dialogic communication can be augmented to reflect the temporal distance between when a user asks a question and when the scientist responds. Additionally, discussions that stem from that answer can be folded into the evaluation of quality engagement. These contextual adaptations of the SCER scale are only the beginning. The full range of applications can only emerge from community use and continual research.

Chapter IX: Conclusion

Now that extant research has been done that investigates key contributors to scientists' willingness to engage with the public (Copple et al., 2020), the focus has now turned to better quality engagement for science communication trainers. The SCER scale can help answer that call. Knowing that the public thinks about science communication engagement similarly to the research explicated in this dissertation, indicated from the scale construction and descriptive statistics reported in the results, trainers can begin to use the SCER scale as an evaluation tool in their curriculum. This tool is ideally used after a training participant conducts a practice talk or presentation. The trainers and other participants can then score the presentation on the SCER scale. Scores low in one area may be important to improve based on scientists’ goals or objectives. The scale can evaluate scientists' communication engagement as a type of checklist for each dimension represented, where each item represents an area of science communication engagement. If scientists want to improve their engagement, they can focus on lower scores from an audience to improve in those areas for higher scores in future activities (either from a practice audience in a training program or their intended audience). Not everyone will score perfectly on every dimension, but scores show where scientists can work on their messaging and communication style. The scores represented by the SCER are not true representations of how engaged an audience was. This might sound counter-intuitive, but the CTT used here says that a latent variable's true score will never be known, and measurement error will always be present in some form or another. Scores from the SCER scale should always be taken as representations to build better engagement and not the true score of audience engagement. That’s why the scale is a response scale; it is a representation of audience response. Nonetheless, the scale results are still usable and valuable to researchers, trainers, and scientists. Researchers can use it as a multi-dimensional measure for science engagement. Trainers should use it as an evaluation tool for the efficacy of their training. And finally, scientists should use it as an evaluation tool for improving their public engagement activities.

This dissertation builds on past research to improve science communication through measurement of high- and low-quality public engagement with science. So much outstanding research was crafted to get to this point. Science communication objectives led to greater understanding of key contributors for scientists engagement intentions (J. C. Besley, Dudo, Yuan, et al., 2018). Public relations and organizational communication built on ideas of two-way dialogue to improve attitudes with stakeholders (Kent & Taylor, 2002; Yang et al., 2015). Digital engagement research outlined a model for user engagement so online communication can improve absorption and sharing content (Jeeyun Oh et al., 2018). And, finally communication engagement provided the framework from individual state engagement to community engagement for ideal society decision making (Johnston & Taylor, 2018). Now that all the pieces are on the table researchers and practitioners can improve with the SCER scale. Twelve dimensions (accessibility, altruism, collaboration, empathy, expertise, framing, genuineness, grounding, interaction, novelty, respect, and transparency) represent science communication engagement from multiple areas of research. These dimensions come together for a wholistic view of PES response from audiences through a 12-item scale. Researchers, science communication trainers, and scientists can have a better idea of their engagement efforts through this scale and the work done in this dissertation. This scale brings clarity to an ambiguous concept, and through the research presented throughout this dissertation, the field has a better idea of how to see the elephant.

Appendix

Table 7. Preliminary table of studies and their definitions of science engagement.

Study	Authors	Year	Publication	Term	Definition
Visual Literacy and Science Communication	Trumbo, Jean	1999	Science Communication	Public Communication of Science and Technology	Communication among scientists and mediated communication from scientists to the public.
Science communication: A contemporary definition	T.W. Burns, D.J. O'Connor, and S.M. Stocklmayer	2003	Public Understanding of Science	Public Communication of Science and Technology	May be defined as the use or appropriate skills, activities, and dialogue to produce one or more of the following personal responses to science: Awareness, Enjoyment, Interest, Opinions, Understanding of science, its content, processes, and social factors.
A typology of public engagement mechanisms	Rowe, Frewer	2005	Science, Technology, and Human Values	Public Engagement with Science	Public engagement is made up of three significant activities differentiated by the nature and flow of information between the exercise sponsors and public participants: communication, consultation, participation.

What Factors Predict Scientists' Intentions to Participate in Public Engagement of Science Activities?	Poliakoff and Webb	2007	Science Communication	Public Engagement with Science	Any scientific communication that engages an audience outside of academia.
Many Experts, Many Audiences: Public Engagement with Science and Informal Science Education	McCallie, Bell, Lohwater, Falk, Lehr, Lewenstein, Needham, and Wiehe	2009	CAISE Inquiry Group Report	Public Engagement with Science	Activities, events, or interactions characterized by mutual learning—not one-way transmission from “experts” to publics—among people of varied backgrounds, scientific expertise, and life experiences who articulate and discuss their perspectives, ideas, knowledge, and values.
Can science communication workshops train scientists for reflexive public engagement? The ESConet experience	Miller, Fahy, and the ESConet Team	2009	Science Communication	Public Engagement with Science	Effectively communicate with the mass media, policy makers, and various lay public through a more dialogue-based communication style
What's next for science communication? promising directions and lingering distractions	Nisbet, Matthew C.; Scheufele, Dietram A.	2009	American Journal of Botany	Public Engagement with Science	Initiatives that sponsor dialogue, trust, relationships, and public participation across a diversity of social settings and media platforms.

The mobilization of scientists for public engagement	Bauer and Jensen	2011	Public Understanding of Science	Public Engagement with Science	A continuum of communicative genres from arcane technical laboratory discussions on the one end (conference presentations, and published literature) to lectures and writings for wider audiences outside the peer group on the other end, with no clear “cut” indicating where “science” ends and “popularization” or PE begins
Which indicators for the new public engagement activities? An exploratory study of European research institutions	Neresini and Bucchi	2011	Public Understanding of Science	Public Engagement with Science	No clear definition. Research is exploratory and qualitative in nature and does leaves public engagement activities open ended in a survey of EU scientists.
What Science Communication Scholars Think About Training Scientists to Communicate	John C. Besley and Andrea H. Tanner	2011	Science Communication	Public Engagement with Science	Interaction with the public or any subject matter non-expert.
Scientists' motivation to communicate science and technology to the public: Surveying participants at the Madrid Science Fair	Martín-sempere, María José; Garzón-garcía, Belén; Rey-rocha, Jesús	2011	Public Understanding of Science	Public Understanding of Science	Improve the general public’s access to science and should encourage them to take part in activities to improve the public understanding of science (PUS), and even consider it their duty to do so.

					Social identification with scientific institutions and their actors, which is dependent upon reciprocal trust in the line of the so-called “contextual approach” to PUS
Toward a Model of Scientists' Public Communication Activity: The Case of Biomedical Researchers	Dudo, Anthony	2012	Science Communication	Public Communication of Science and Technology	Communication of science by scientists to people not involved with research in their field
Predicting scientists' participation in public life	Besley, John C; Oh, Sang Hwa; Nisbet, Matthew	2012	Public Understanding of Science	Public Engagement with Science	Borrows a term of "democratic engagement" that includes community-level civic behavior (e.g., volunteering for a non-profit) that may not be specifically political. Political behavior aimed at influencing public decision-making (e.g., contacting officials, attending a public meeting).
Enhancing learning, communication and public engagement about climate change - some lessons from recent literature	Wibeck	2013	Environmental Education Research.	Public Engagement with Science	A contextual dialogue model where the public needs to actively take part in learning and action on climate change; engagement involves "minds, hearts and

					hands."
An Instrument for Assessing Scientists' Written Skills in Public Communication of Science	Ayelet Baram-Tsabari and Bruce V. Lewenstein	2013	Science Communication	Public Communication of Science and Technology	The ability to use nontechnical language and norms when discussing science beyond the scientific community. Clearer speakers and engaging in a respectful dialogue with the public, as public values make important contributions to science-related policy issues
How scientists view the public, the media and the political process	Besley, John C; Nisbet, Matthew	2013	Public Understanding of Science	Public Engagement with Science	Public engagement includes a host of activities wherein citizens are asked to play a role in decision-making. It can take the form of one-way attempts to provide content through the news media, advertising, Internet sites, or presentations, to more interactive activities where participants are invited to participate in two-way dialogue
Portrayals of Technoscience in Video Games: A Potential Avenue	Anthony Dudo, Vincent Cicchirillo, Lucy	2014	Science Communication	Public Understanding of Science	Engage with science in novel, memorable ways that contribute to their

for Informal Science Learning	Atkinson, and Samantha Marx				understanding, perceptions, and behaviors relative to STEM issues.
An analysis of nonscientists as public communicators	Dudo, Anthony; Kahlor, Lee Ann; Abighannam, Niveen; Lazard, Allison; Liang, Ming Ching	2014	Nature Nanotechnology	Public Communication of Science and Technology	Engage with a broader array of publics in meaningful conversations about nano innovations and the risks, benefits, and regulatory challenges they pose2
What do scientists think about the public and does it matter to their online engagement?	Besley	2015	Science and Public Policy	Public Engagement with Science	Defined broadly to include any type of planned interaction where scientists communicate with adult non-scientists about science and technology outside of a classroom setting
Scientists' views about communication training	Besley, Dudo, and Storksdieck	2015	Journal of Research in Science Teaching	Public Engagement with Science	Science engagement and science communication, defined as an opportunity for dialogue and interaction between science-based professionals and the public.
Science in Culture: Audiences' Perspective on Engaging With Science at a Summer Festival	Sardo and Grand	2016	Science Communication	Public Engagement with Science	No clear definition. Public engagement with science can happen in traditional venues, both for-mal, such as schools, universities, or research centers, and

					informal, in places associated with science, such as science centers and museums.
Scientists' prioritization of communication objectives for public engagement	Dudo and Besley	2016	PLoS ONE	Public Engagement with Science	Meaningful interactions with the public to produce greater empathy for the perspective of the other.
Qualitative Interviews With Science Communication Trainers About Communication Objectives and Goals	John C. Besley, Anthony D. Dudo, Shupei Yuan, and Niveen Abi Ghannam	2016	Science Communication	Public Communication of Science and Technology	Effective communication or engagement about science. Creating opportunities for dialogue between scientists and their broader communities
Information-Sharing and Community-Building: Exploring the Use of Twitter in Science Public Relations	Leona Yi-Fan Su, Dietram A. Scheufele, Larry Bell, Dominique Brossard, and Michael A. Xenos	2017	Science Communication	Public Engagement with Science	Operating within the broader paradigm of science communication, science public relations efforts such as news releases and blog posts may help increase public engagement with science, enhance public understanding and awareness of it, and embed it in day-to-day culture
Two-way communication between scientists and the public: a view from science communication trainers in North	Yuan, Shupei; Oshita, Tsuyoshi; AbiGhannam, Niveen; Dudo, Anthony; Besley, John C; Koh,	2017	International Journal of Science Education, Part B: Communication and Public	Public Engagement with Science	Emphasizes interactive communication and mutual understanding between two parties. Our underlying assumption is that

America	Hyeseung E		Engagement		the emphasis on two-way communication has the potential to improve how scientists think about and approach science communication
Who Are You Writing for? Differences in Response to Blog Design Between Scientists and Nonscientists	Anna Gardiner, Miriam Sullivan and Ann Grand	2018	Science Communication	Public Engagement with Science	Mediators of science for nonscientist readers. It also provides evidence-based suggestions for science bloggers who want to use their science blog to help disseminate scientific information to a wider audience and who most frequently perceive themselves as science explainers and educators.

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